Essays in Economic Demography

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The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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List of Abbreviations

BOND Benefit Offset National Demonstration

CAMSIS Cambridge Social Interaction and Stratification Scales

CPP-D Canadian Pension Plan Disability insurance program

DI Disability Insurance

DiD Difference-in-differences

HISCAM Historical CAMSIS

HISCLASS Historical International Social Class Scheme

HISCO Historical International Standard Classification of Occupations

LAD Longitudinal Administrative Database

LHS Left-hand side

NYSIIS New York State Identification and Intelligence System

QPP-D Quebec Pension Plan Disability insurance program

RHS Right-hand side

RoC Rest of Canada (excluding Quebec)

SEP Socioeconomic Position

SGA Substantial Gainful Activity

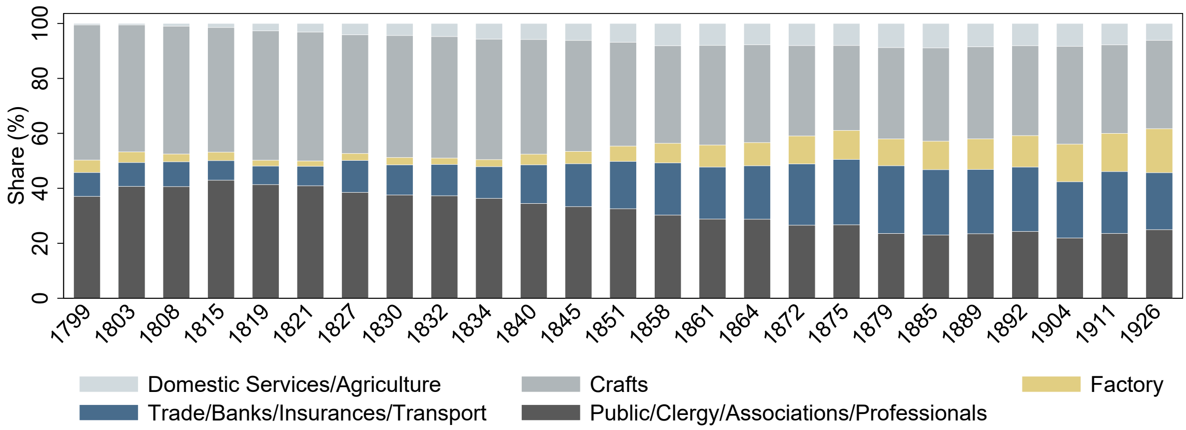
Chapter 1

Dissertation Overview

This dissertation, *"Essays in Economic Demography"*, addresses two subjects in economic demography: intergenerational mobility and disability insurance. In Chapters 2 and 3, I explore changes in intergenerational occupational mobility in Zurich over the nineteenth century and how estimates of mobility might be affected by different kinds of sample selection, respectively. Chapter 4 studies the welfare implications of different incentive structures in modern disability insurance systems. The unifying feature of all three chapters is that they shed light on different aspects of social inequality. Social mobility can be seen as inequality of chances with respect to social advancement, and disability insurance is concerned with inequality in health. Chapters 2 and 3 approach their research questions empirically, whereas Chapter 4 features a theoretical approach paving the way for empirical implementations.

Chapter 2 explores how occupational mobility changed among the citizens of Zurich over the course of the nineteenth century. It is joint work with Joël Floris and Ulrich Woitek and is titled *"Intergenerational Mobility in the Nineteenth Century—Micro-Level Evidence from the City of Zurich"*. Economic inequality has been strongly increasing over the past few decades and is currently at a similar level as at the end of the nineteenth century (Piketty, 2014). The concept of intergenerational mobility is interrelated with economic inequality in two ways. First, mobility quantifies how permeable the social structures are, and thus how inequality might evolve over time. Second, lack of social mobility can be interpreted as inequality of chances to achieve economic success. Consequently, investigating intergenerational mobility is crucial to understanding inequality. Intergenerational mobility is, by construction, a topic that has to be addressed with historical data. One needs information on at least two generations to quantify the level of mobility. In order to examine changes in social mobility, one has to go back in time even further. A period mirroring the extent of the current structural change is the nineteenth century. While today's enhancement of computers and information technology induces a shift in the sectoral distribution of occupations, the expansion of steam power, factories, and the financial sector did as much during the nineteenth century (see e.g. Ashton, 1997; Mokyr, 1998; Brynjolfsson and McAfee, 2012; Dorn, 2015, and Figure 1.1 for the sectoral change in nineteenth century Zurich). Analyzing this historical period might, thus, yield insights into the evolution of intergenerational mobility in times of major structural change.

FIGURE 1.1. OCCUPATIONAL DISTRIBUTION OF ZURICH CITIZENS ACROSS SECTORS 1799–1926.



Note: This figure depicts the rise of the industrial sector (Factory) and the financial sector (Trade/Banks/Insurances/Transport). The data for the figure originate from the directories of citizens of the city of Zurich described in Chapters 2 and 3. The classification of occupations by sector follows Schüren (1989).

Chapter 2 tackles this question with historical data from Zurich. One of the main contributions of the chapter is the construction of a data base containing extensive panel information on the universe of Zurich's male citizenry over more than one century (1799–1926). Using this novel data, we are the first to analyze social mobility in nineteenth century Switzerland. The data originating from the directories of citizens of the city of Zurich are unique in their richness of detail on each individual citizen, and hence allow us to contribute to the literature on social mobility beyond providing evidence for Switzerland. Most importantly, the data contain information on family relationships, making it obsolete to link generations with automated linking procedures as the intergenerational link is observable. The continuity of the data further enables us to provide measures of mobility at a high frequency (every two to eleven years).

We provide a rich set of measures based on occupations that allows us to reveal structural change and different aspects of social mobility in Switzerland. We shed light on both the level of and the changes in absolute mobility and relative mobility. While absolute mobility refers to mobility as experienced by the individual, relative mobility describes a society's openness net of structural change (see e.g. Dribe et al., 2015). We find that Zurich's citizenry exhibited increasing probabilities of transitions towards occupations associated with intermediate socioeconomic status. This partially reflects the structural change increasing the industrial and financial sector as depicted in Figure 1.1. Furthermore, we discover decreasing rates of intergenerational mobility with respect to all absolute and relative measures. This result suggests that the fathers' occupational outcomes gained importance for the sons' outcomes among Zurich citizens despite the new opportunities generated by the industrialization process (Kury, 2012), and the comparably progressive political climate in the city of Zurich (Behrens, 2015). A key driver of this change was that sons with low socioeconomic background experienced strong and increasing intergenerational persistence. Our estimates on the level of mobility for Zurich lie between the existing estimates for the United States, Norway, and the United Kingdom in the late nineteenth century (Long and Ferrie, 2013; Modalsli, 2017).

Chapter 3 is titled *"Bias in Social Mobility Estimates with Historical Data—Evidence from Swiss Microdata"* and is closely related to the previous chapter. I investigate the same data from a more technical point of view, exploiting the uniqueness of the data base. In particular, Chapter 3 explores how estimates of social mobility are affected by three potential sources of bias: (1) migration, (2) occupational life-cycle patterns, and (3) automated record linkage procedures. Many existing studies on social mobility cannot account for some, or even all, of these issues. This raises the questions if the estimates that result from such studies are significantly biased and, if so, in which direction. The results of this chapter provide insights on how serious these concerns are. Thus, they allow researchers in the field of intergenerational mobility to put their results into context. To the best of my knowledge, no comparably comprehensive evaluation of potential sources of bias in social mobility estimates exists, especially in a historical context.

Why should one be concerned about bias due to migration, life-cycle patterns in occupations, or linking procedures? First, migrants are usually omitted from analyses of intergenerational mobility because they are no longer observable in the data. Consequently, migration affects estimates of social mobility if migrants experience a different level of social mobility than non-migrants. The Zurich data keep track of Zurich's citizens even when they move abroad, allowing me to quantify the potential for bias by comparing the estimates of the two groups. Indeed, I find that migrants overproportionally came from families with a higher socioeconomic status (as measured by the father's position) and entered intermediate socioeconomic positions more often than non-migrants. This selection of migrants is similar to what has been found for nineteenth century Germany (Wegge, 1999, 2002, 2010). Furthermore, migrants exhibited higher levels of intergenerational mobility as compared to non-migrants, and the former experienced lower rates of upward mobility than the latter. This could indicate that emigrants experienced a difficult start in the country of destination and potentially also a slow rate of assimilation (see e.g. Borjas, 1992, 1993, 1994, 1995). Additionally, I find large differences with respect to selection and exhibited levels of social mobility of emigrants by destination continent. Swiss migrants to other European countries were selected in a particularly positive way with respect to both the SEP of the father and the son as compared to emigrants to Canada and the United States. Similarly, the former were 1.12 times more likely to experience upward mobility vs downward mobility, while the latter were 1.59 times more likely to experience downward vs upward mobility. All of these findings indicate that focusing the analysis of intergenerational mobility on geographically immobile individuals leads to a selection of the socially less mobile part of the population. The resulting bias when omitting emigrants lies between 1 and 10 percent in the Zurich data.

Second, individuals' socioeconomic position may change over the course of their lives (intragenerational mobility). Taking this pattern into consideration requires multiple observation of an individual—a property that historical data usually do not provide. The Zurich data allow to observe citizens repeatedly. Thus, I can investigate these life patterns, and whether they translate into differential estimates of social mobility. I observe that, with increasing age, individuals entered occupations associated with higher socioeconomic status. Evaluating the level of father-son mobility conditional on both the father's and the son's age at classification reveals that some of the social mobility estimates are affected by the life-cycle patterns. The point estimates change up to 10 percent with different classification ages. However, neither the father's nor the son's classification age exhibit a monotone correlation with the direction of the bias.

Third, most studies on social mobility depend on linking several distinct data sets to obtain information on two or more generations. As the procedures used for these record linkages are imperfect, estimates of social mobility may be affected significantly (see e.g. Eriksson, 2017; Massey, 2017; Bailey et al., 2019). The observable intergenerational link in the data at hand enables me to put these mechanisms to the test by separating and automatically re-linking father-son pairs. State-of-the-art linking procedures exhibit high rates of correct matches (between 77 and 95 percent) in the Zurich data. However, these high (correct) match rates are mostly caused by the fact that sons can be identified easily by the characteristics employed for the matching procedures (correct name, year of birth, and place of family origin). Other sources of data usually do not allow for such an easy identification as they contain misspelled names, small deviations in the inferred year of birth, and information on place of birth rather than place of family origin. Consequently, I do not observe significant bias in social mobility estimates, but employing data with less detailed information on individuals may still induce significant bias, as e.g. Bailey et al. (2019) point out.

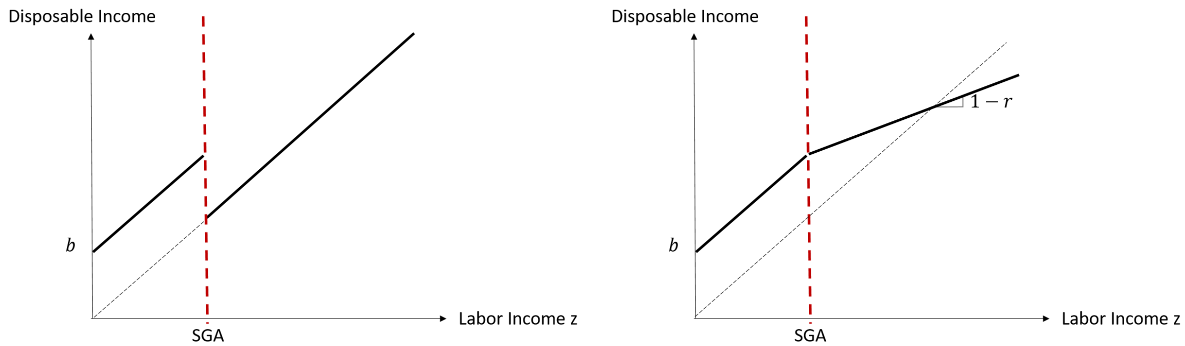
All in all, one should be cautious when estimating intergenerational mobility without taking migration or life-cycle patterns in socioeconomic positions into account. Linking procedures may also induce bias depending on the quality and quantity of the data to be linked (Bailey et al., 2019). The relative size of the migration bias and the life patterns bias is comparable with a deviation of up to 10 percent, while the bias induced by linking procedures lies consistently below 1 percent of the baseline in the Zurich data.

Chapter 4 tackles the topic of incentives in disability insurance (DI) systems. It is joint work with Andreas Haller and Stefan Staubli and is titled *"Offsetting the Cliff? A Sufficient Statistics Approach to Measuring the Welfare Effects of Work Incentives in Disability Insurance"*. On the one hand, both the beneficiary population and the expenditures of DI have been rising continuously in recent decades (Autor et al., 2018). For example, the share of the working age population receiving DI benefits has increased from below 1 percent to almost 5 percent in the United States and from 1 percent to 7 percent in the United Kingdom over the past five decades (Autor et al., 2018). On the other hand, disability insurance systems in many countries feature strong work disincentives unnecessarily dampening the labor supply of disability insurance recipients (Autor and Duggan, 2003; Bound et al., 2010). According to Autor and Duggan (2006), three potential ways to curb the increasing costs of DI programs are: (1) increasing incentives to work while receiving DI, (2) reducing incentives to enter DI, and (3) introducing stricter eligibility standards. In this project, we focus on the first of these routes, providing (financial) incentives for DI recipients to return to work. We develop a sufficient statistics model that allows us to estimate the welfare impact of such a policy.

The strong work disincentives in most DI programs mentioned above usually come in the form of so-called “cash cliffs”. If a DI recipient’s labor income crosses a certain income threshold (the so-called earnings disregard), she loses her entire cash benefits. Introducing a “benefit offset program” increases work incentives by reducing DI recipients’ cash benefits more gradually beyond the earnings disregard (see Figure 1.2 for stylized budget sets under a cash cliff and a benefit offset system). Norway and the United States are two recent examples of countries that tested replacing the cash cliff system with a benefit offset. Norway introduced a benefit offset that allowed DI beneficiaries to keep NOK 0.40 of every NOK 1.00 earned beyond the earnings disregard, resulting in substantial increases in labor supply (Kostol and Mogstad, 2014). In the United States, a $ 0.50 for $ 1.00 benefit offset has been evaluated in the large scale benefit offset national demonstration (BOND) field experiment. Gubits et al. (2018) report small increases in labor supply resulting in similarly small increases in earnings of DI beneficiaries but increased program costs. In general, the introduction of a benefit offset may have two opposing effects. First, individuals currently receiving DI benefits might be incentivized to supply more labor (labor supply effect). Second, the DI program becomes more attractive overall, which may attract applications and thus entry to DI (induced entry effect). In our model, we formalize this trade-off and present robust sufficient statistics formulas that capture the insurance value and incentive costs of such a policy reform. We find that the earnings elasticity of DI recipients is a sufficient statistic for the labor supply effect, and that the DI benefit take-up elasticity is a sufficient statistic for the induced entry effect. Hence, estimating these elasticities facilitates evaluating the welfare effects of “offsetting the cliff”.

Figure 1.2. Budget sets under cash cliff vs benefit offset system.

(a). Cash cliff. (b). Benefit offset.



Note: b denotes the base DI benefits, SGA the earnings disregard, and r the offset rate. The benefit offset system reduces income beyond the earnings disregard gradually (panel 1.2b) while the cash cliff features a discontinuous drop (panel 1.2a). The dashed 45 degree line represents the budget set of individuals not receiving DI benefits.

Canada operates two distinct disability insurance programs: the "Quebec Pension Plan DI program" (QPP-D) for Quebec and the "Canadian Pension Plan DI program" (CPP-D) for the Rest of Canada (RoC). Two policy reforms in the CPP-D led to exogenous variation in the benefit level (in 1987) and in the earnings disregard (in 2001) in RoC but not in Quebec. This exogenous variation can be exploited in a difference-in-differences approach with administrative data to estimate both elasticities for a welfare analysis. We provide a summary of the data, the policy reforms, and an outlook on the empirical approach in Chapter 4. Using estimates on the United States from the existing literature, we find that the introduction of a benefit offset system is unlikely to reduce program costs, which is in line with the evaluation of the BOND field experiment (Gubits et al., 2018). Still, we find that such a policy might improve welfare, which has not been and cannot be evaluated with the BOND experiment.

The unifying feature of all three chapters is that they shed light on different aspects of social inequality. As the seminal work by Piketty (2014) has pointed out, the past few decades have seen an increase in the inequality of individual economic outcomes both within and between countries. One of the keys to explaining the extent of social inequality is intergenerational mobility. Recent numbers suggest that only 15 percent of children with parents that did not complete secondary school achieve a university degree across OECD countries. This number compares to 60 percent if at least one of the parents obtained a university degree (OECD, 2018).[1] Chapters 2 and 3 of my thesis aim at providing this vibrant policy debate with evidence from historical data.

Chapter 4 is a contribution to the debate of optimal social insurance policy. This debate has important implications for inequality as well. First, a large body of literature explores whether there is a relationship between health, thus disability, and economic inequality with causality potentially running in both directions (Deaton, 2003; Leigh et al., 2009). Second, impairments to health and disability have been found to decrease labor supply and thus wages or disposable income of individuals (Currie and Madrian, 1999). This reduction in disposable income may aggravate economic inequality if the poor are more likely to be hit by health shocks. Even if disability shocks are equally distributed, they induce, ceteris paribus, economic inequality by resulting in differential levels of disposable income. Third, health insurance and DI may affect this induced inequality in two ways: (1) DI allowance discourages labor supply even more (Maestas et al., 2013), increasing wage inequality, but (2) DI benefits compensate for earnings loss and have been found to increase disposable income (Kostøl and Mogstad, 2015). Consequently, the optimal design of DI systems is of crucial importance to reducing health induced economic inequality. In Chapter 4, we explore whether adjusting labor incentives in current disability insurance programs can improve welfare.

Another common feature of all chapters in this dissertation is their empirical approach. The analysis of intergenerational mobility requires historical data entailing information on at least two life spans. To shed light on the change in mobility, one has to go back in time even further. Consequently, Chapter 2 addresses changes in intergenerational mobility employing data covering the entire nineteenth century. To provide insights as detailed and complete as possible, we employ data featuring true intergenerational links and a large variety of individual-level information observed repeatedly over time. These features of the data turn them into a formidable basis to investigate the questions in Chapter 3, as well. The possibility to track individuals both across the globe and over time and the observable intergenerational links facilitate quantifying the relative size of bias in mobility estimates due to migration, life-cycle patterns, and automated linking procedures. The employed data base is unique in allowing to address all of the three sources jointly. While the main part of Chapter 4 is of theoretical nature, we provide an outlook on how we

[1] Interestingly, recent research has shown that even DI claiming is transmitted across generations (Dahl and Gielen, 2018).

plan to empirically implement our sufficient statistics approach. Estimating the labor supply and the benefit take-up elasticity requires detailed individual-level information contained in administrative data. One needs to observe earnings (labor supply), benefit reception, and program entry and exit. Further, one needs exogenous variation in the level of DI benefits. The Canadian case poses as a perfect setup in both dimensions. First, the Canadian Longitudinal Administrative Database (LAD) fulfills all data requirements containing rich individual- and family-level information on 20 percent of all Canadian tax filers between 1982 and 2016. Second, the dual DI system in Canada and two policy reforms only affecting the CPP-D but leaving the QPP-D unchanged provide exogenous variation, which allows us to estimate the two elasticities and thus the welfare effect of introducing a benefit offset scheme.

Another unifying characteristic of all chapters is their aspiration to advance the existing methodology in one way or another. Our analysis in Chapter 2 provides a more continuous measure of intergenerational mobility than previous historical studies, to the best of our knowledge. This methodological innovation crucially depends on the longitudinal nature of our data: we observe not only subsequent generations, but also each generation over its life cycle. The detailed analysis of an entire period rather than disjoint snapshots at specific points in time is supposedly closer to the evolution of social mobility. Our results accentuate this impression by displaying a relatively smooth transition in the level of mobility over time. Chapter 3 unites the investigation of three separate sources of potential bias. Again, this unification is possible because of the richness of the employed data. While separately addressing the three sources of bias is important, only a comparison of the three may indicate which concerns are the most pressing. Additionally, the split of emigrants by destination continent presents novel insights in the selection of migrants in a historical context. Finally, Chapter 4 advances the existing methodology by expanding existing models of disability insurance (Diamond and Sheshinski, 1995; Parsons, 1996; Inderbitzin and Wallimann, 2013). Our model allows to study the effect of work incentives on labor supply at the intensive margin and provides estimable sufficient statistics formulas. The baseline model is robust to a wide set of extensions. Further, we aim at directly estimating the induced entry effect, which has usually been performed with structural models (e.g. Hoynes and Moffitt, 1999 or Benitez-Silva et al., 2010).

Eventually, all chapters pave the way for future research. Chapter 4 provides a sufficient statistics model to evaluate welfare effects of replacing a cash cliff with a benefit offset system in DI. The model can be employed to estimate these effects in all countries that feature such a cash cliff in their DI programs and provide the appropriate data. Furthermore, future research may extend the model to similar programs, e.g. the "Marginal employment" in Germany that allows workers to earn up to €450 exempt from income tax. For Chapters 2 and 3, we constructed a data base containing the universe of Zurich's male citizenry and a large fraction of its registered inhabitants in the nineteenth century. The data collection is still ongoing, but the data base is already unique in its level of detail and amount of information. The data contain first name, middle names, last name, year of birth, year of death, place of family origin, exact address in the city of Zurich or place of residence outside the city, occupations, military affiliations, public offices, number of children, number of houses owned, spouses' names, and references to all living (and some deceased) relatives of all male citizens of the city of Zurich between 1799 and 1926. Hence, estimating the level of social mobility and the size of potential bias is merely scratching the surface of possible research questions that can be addressed with these data. For example, one might investigate family size, mortality, life expectancy, assortative mating, and intragenerational mobility in greater detail. Furthermore, these chapters indicate how many (data) treasures may be found in historical archives.

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Chapter 2

Intergenerational Mobility in the Nineteenth Century Micro-Level Evidence from the City of Zurich

Joint with Joël Floris and Ulrich Woitek

Abstract: We construct a data base of Zurich citizens and analyze their level of social mobility between 1819 and 1879. The data allow us to repeatedly observe the over 20,000 individuals irrespective of their place of residence. We provide a continuous measure of intergenerational mobility for a homogeneous population. Focusing on such a homogeneous group ensures that the estimates of mobility are comparable over time. Further, we provide a first estimate on the extent of social mobility of Zurich's resident population and compare it with our estimates for the citizenry and existing estimates for other countries. We find decreasing levels of intergenerational occupational mobility over time both among Zurich's citizens and resident population. The reduction in mobility is comparable to the cross-country difference between the United States and the United Kingdom at the time.

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JEL classification: Intergenerational Mobility, Occupations, 19th Century.

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2.1 Introduction

Economic inequality is on the rise again, reaching levels similar to those present at the end of the nineteenth century (Piketty, 2014). Lack of intergenerational mobility is a very important aspect of inequality as for example pointed out by Piketty (2014, p. 65). Hence, analyzing social mobility is central to understanding inequality. We describe changes in the level of occupational mobility of Zurich's citizenry and resident population over the course of the nineteenth century employing a broad set of measures. Our contribution is fourfold. First, we constructed a comprehensive data base containing rich information on the universe of Zurich's adult male citizenry and most registered residents at several points in time between 1799 and 1926 (see e.g. Figure 2.2 for the specific time points). Second, the detailed information allows us to categorize individuals with respect to occupation and to construct comparably frequent measures of intergenerational mobility (every two to eleven years). The measures provide a more continuous picture of changes in mobility than usually analyzed in the literature. Most studies rely on between two and five key years (e.g. Long and Ferrie, 2013) whereas our data cover twenty-five allowing us to estimate mobility in fifteen time points. Third, we provide results that do not rely on a linking mechanism between generations, because we directly observe family relationships guaranteeing unbiased estimates. Fourth, we shed light on the level and changes of mobility in nineteenth century Switzerland with Zurich as a case study and compare our results to estimates for Argentina, Norway, the United Kingdom, and the United States. Our main finding is a decrease in father-son mobility, mainly driven by the intergenerational persistence of occupations with low socioeconomic position (SEP). In the late nineteenth century, our estimates are comparable to the estimates for Norway (Modalsli, 2017) and the United Kingdom (Long and Ferrie, 2013).

As Switzerland in general (e.g. Veyrassat, 2012), the city of Zurich experienced rapid economic development during the nineteenth century, accompanied by structural change. In the period from 1812 to 1888, the population of the city and its surrounding municipalities increased more than tenfold with a large population boom starting around mid-century (see Figure 2.1). After the incorporation of the surrounding municipalities into the city area in 1893, Zurich became the most populous city of Switzerland with over 100,000 inhabitants (Behrens, 2015). Zurich turned not only into an economic metropolis but also a financial center, traffic hub, and a major center of education and research

(Behrens, 2015; Illi and König, 2017). Phenomena such as the growth of the textile industry, the construction and expansion of the railway, the formation of the *Credit Suisse* and similar institutions, and the foundation of the two universities (University of Zurich and ETH Zurich) were both causes and consequences of immense economic growth. On the federal level, the constitution of 1848 and its revision in 1874 set the institutional framework for this development, with reforms such as the introduction of the freedom of movement and the freedom of trade (Kley, 2011; Kury, 2012). Zurich's political history in the nineteenth century was marked by a progressive democratization. Liberal forces were able to break the political power of the conservative forces in the 1830s. After the liberal founding of the federal state in 1848, the political dominance of the liberals and the representative system that they shaped were reversed in Zurich in the 1860s by the introduction of direct-democratic instruments (Behrens, 2015).

What are the consequences of these economic and institutional changes for social mobility? Going as far back as to de Tocqueville's work from 1835 on the democracy in America, there is the expectation of a positive relationship between democracy and mobility. Similarly, one would expect industrialization to increase both upward and downward mobility. As Landes (2003, p. 546) puts it, "*A competitive industrial system* [...] *will increase social mobility, raising the gifted, ambitious and lucky, and lowering the inept, lazy, ill-fortuned*".

However, the recent literature shows that these expectations might be misleading, and our results provide further evidence for this finding. Acemoglu et al. (2017) demonstrate that democratic processes can actually reduce social mobility. With respect to industrialization in the United States, Blau and Duncan (1967) suggest increasing levels of mobility. The British example provides mixed evidence. While Long (2013) finds very high mobility rates during the Industrial Revolution, the results of Humphries (2010, p. 222–229), Clark (2014), Clark and Cummins (2014, 2015), and Clark et al. (2015) point in the opposite direction. On the other hand, Dribe et al. (2015) finds that absolute and relative mobility in rural Sweden increased with industrialization. According to Schüren (1989), larger German cities exhibited reduced chances of intergenerational mobility after 1870, while horizontal job mobility increased.

There is a large body of research on social mobility in the fields of economics, history, and sociology.[1] For the main part of our analysis, we follow the approach of Long and Ferrie (2013) and Modalsli (2015, 2017) employing transition matrices. Long and Ferrie (2013) show large differences in the evolution of social mobility between the United Kingdom and the United States. The estimates for Norway provided by Modalsli (2017) show that Norway's level of mobility was comparable to the United Kingdom. Pérez (2019) employs the same strategy to show that social mobility was larger in Argentina in the late nineteenth century than in Norway, the United Kingdom, and the United States. Clark (2014) and Clark et al. (2015) propose to use the persistence of surname shares in elite groups as a measure for mobility, which, to some extent, overcomes the problem of attenuation bias (e.g. Clark, 2014, p. 108–113). Barone and Mocetti (2016) apply this method to study long-run intergenerational mobility in the city of Florence. These studies show a very high persistence in social status over time. Olivetti and Paserman (2015) analyze father-daughter mobility in the nineteenth century US employing a novel strategy related to first names. Dribe and Svensson (2008), Dribe et al. (2015), Dribe and Helgertz (2016), Lindahl et al. (2015), and Adermon et al. (2018) describe mobility in nineteenth century Sweden. Among these, Dribe and Helgertz (2016), Lindahl et al. (2015), and Adermon et al. (2018) contribute to the fast growing branch of research on multi-generational mobility exploring a potential influence of grandfathers and distant relatives.[2]

The studies of Falcon (2012, 2013, 2016), Jann and Combet (2012), and Jann and Seiler (2014) analyze intergenerational mobility in Switzerland during the twentieth century. While Falcon (2012, 2013, 2016) finds a relatively constant level of mobility, Jann and Combet (2012) and Jann and Seiler (2014) show either slightly decreasing or u-shaped levels of mobility, depending on the specific categorization. In contrast to the other studies on Switzerland, we analyze mobility in the nineteenth century, and narrow the focus down by restricting the analysis to the citizenry of Zurich. An advantage of this approach is that it provides a more homogeneous sample, which helps reducing the random influences problem pointed out by Clark (2014).

[1] Solon (1999) and Black and Devereux (2011) provide a review on intergenerational mobility.

[2] See Solon (2018) for an overview of the mixed evidence on the causal influence of distant relatives. In this paper, we follow the standard one-generational approach.

The remainder of this paper will be structured as follows. Section 2.2 contains a description of our data base and some descriptive statistics. We present our main results in Section 2.3 with several robustness checks and extensions in the Appendices 2B and 2C. Section 2.4 concludes.

2.2 Data and Descriptive Statistics

Directory of Citizens and Residents of the City of Zurich One contribution of this study is the digitization of twenty-five editions of the directory of citizens of the city of Zurich and thirty-two editions of Zurich's directory of registered residents covering the period 1799–1926 (original title: *Verzeichniß der Bürger der Stadt Zürich* and *Verzeichniß der Niedergelassenen der Stadt Zürich*).[3] These directories were originally created through a collaboration of several former government officials, scholars, and the municipal authority. The directories contain information on all of Zurich's adult male citizens, i.e. individuals holding Zurich citizenship, and registered residents, i.e. people officially living in the city of Zurich at that time. The information was collected through official records, interviews, and mail-in forms and was regularly updated (see e.g. Hofmeister, 1819).

The information in the directories entails a list of all male relatives[4], the first and last names, the year of birth, the year of death, occupations, military affiliations, public offices, the number of houses owned, the family origin, and the living address within Zurich. For citizens, the directories even contain the place of residence if individuals lived abroad or generally outside the city allowing to track citizens irrespective of their location.[5] The directories' information enables us to follow individuals over time and to reconstruct the male lineage of almost all citizens and several residents. The direct reference of all male relatives is a major advantage when analyzing social mobility, as we do not rely on any linking mechanism between generations which guarantees representativeness (see Chapter 3 or e.g. Bailey et al., 2017 on this matter). Unfortunately, the information on women

[3]The digitization is still ongoing for one part of the residents' directories and the earliest (before 1819) and latest (after 1892) citizens' directories.

[4]The information on residents is less detailed. It only features a list of all sons irrespective of their current location. A reference to further male relatives is only provided if they also resided in Zurich.

[5]Information on emigrants was acquired partially through foreign authorities, partially through relatives in Switzerland, and partially by mail-in forms. If no current information was available, the directory contains the latest available characteristics. Further, it contains a note stating that this specific citizen was untraceable at the time and the last date of notice.

is sparser. Only widows and unmarried adult daughters whose father already deceased are directly contained in the directories. Otherwise, women are indirectly referred to as daughters or wives of male citizens and residents without much detail (only name, year of birth, and place of origin).[6]

In total, our citizen data set contains over 20,000 individuals born between 1708 and 1926, constituting more than 10,000 father-son pairs and 6,000 different families covering up to 7 generations. The residents data contain over 10,000 individuals born between 1723 and 1869 and constitute roughly 2,500 father-son pairs with information on both father's and son's occupation. We classify the occupation of both fathers and sons according to a procedure described below (p. 21). In order to obtain a continuous measure of intergenerational mobility, we examine fathers' occupations in every available key year and combine these father-observations with the corresponding son-observations. Consequently, we estimate the level of intergenerational (father-son) mobility for every father that lived at a specific point in time. The corresponding son-observations are not fixed by observation year but rather the approximate age of the son. Namely, we classify the occupation of each father's sons' in the year closest to their fortieth birthday.[7] This procedure is supposed to reduce life-cycle bias due to intragenerational occupational mobility (see Chapter 3).

The resulting data base allows us to quantify social mobility of two sub-populations. First, one can construct a sample that is comparatively homogeneous over time and not bound to one specific location by including only father-son pairs whose families held Zurich citizenship already before one specific point in time, in our case 1820. The advantage of this selection is that the sample's homogeneity helps to smooth out random influences on social status (Clark, 2014, p. 108–113). As living outside of Zurich did not lead to an automatic loss of citizenship, this sample does not exhibit selection of geographically immobile individuals (see Chapter 3). This first sample is featured in our main analysis, as we want to emphasize the time aspect in the change of social mobility over the century. Second, one can construct a census sample for the city of Zurich containing both resi-

[6]Consequently, we miss the intergenerational transmission through the female side as presented in e.g. Chadwick and Solon (2002) or Dribe et al. (2017). Similarly, we cannot analyze transmission from parents to daughters as Chadwick and Solon (2002) or Olivetti and Paserman (2015).

[7]We exclude individuals whose occupation is only available before the age of twenty or after the age of sixty-five (185 observations).

dents and resident citizens.[8] This sample allows to focus on the level of intergenerational mobility of the permanent resident population within Zurich. However, the geographic fluctuation rate was high. Thus, only few registered residents are linkable to their father, and the sample excludes all citizens that emigrated from the city. Consequently, we treat the second sample merely as a comparison group for both the main analysis and other international studies on social mobility in the nineteenth century and discuss the results in Appendix 2C.

Citizen Status in Nineteenth Century Zurich As we restrict our main analysis to citizens, the characteristics of citizens need to be introduced in greater detail. With respect to the institutional framework, the citizens of Zurich comprised a relatively homogeneous group. They shared the same rights and had to fulfill the same obligations. The rights of a citizen included voting rights (for males), access to pauper relief, and the right to use community resources. One key difference between residents and citizens was that residents were not allowed to vote on the municipality level. Citizenship in the city of Zurich could be obtained in three ways (Wirth, 1871-1875, Vol. 2, p. 29–33): (1) by birth, (2) by marriage to a citizen (for women), or (3) by paying a fee. Female citizens lost the citizenship in their home municipality when marrying a citizen from another municipality. The fee was high and could vary within certain limits. The level depended on regional origin: it was highest for foreigners, intermediate for citizens from other Swiss cantons, and lowest for citizens from other municipalities within the canton of Zurich. Thus, it provided a barrier to geographical mobility and naturalization.[9] Besides having to pay the fee, individuals wishing to join the municipality had to proof good reputation and pass a property threshold. In addition, future citizens had to prove their membership in the Christian church until 1866.

Descriptive Statistics and Trends Similar to the bulk of the social mobility literature in a historical context, we base our estimates on occupation data instead of income

[8] Besides citizens and registered residents, the population of a municipality also consisted of foreign temporary residents (in German: *Aufenthalter*). Individuals belonging to the third group are not traceable through official records as their stay in Zurich was of a limited amount of time.

[9] In 1813, the fee of purchasing the citizenship was 1,500 Gulden for former citizens of other municipalities within the canton of Zurich, 2,000 Gulden for citizens from another Swiss canton, and 2,500 Gulden for foreigners (Hofmeister, 1813). Using the official exchange rate of Gulden to the Swiss Franc of 2.29 (Bundesblatt 1851, 1(18) 335ff), we can compare the fees with data from tax registers. We find that only very few top earners within the city had an annual income comparable to these levels.

or education (see e.g. Ferrie, 2005; Dribe and Svensson, 2008; Dribe et al., 2015; Long and Ferrie, 2013; Modalsli, 2017; Pérez, 2019). The restricted information provided by tax directories does not suffice to reliably quantify intergenerational mobility over the entire period and educational data is even scarcer. Thus, our analysis of social mobility is based on a classification of occupations into several categories. In the main part of our analysis, we employ a categorization of occupations appropriate for the German speaking area that is based on Schüren (1989). This classification divides occupations into three socioeconomic positions (SEP): low, middle, and high SEP.[10] The low SEP category contains laborers, craftsmen, and servants. The most frequent occupations are locksmith, mechanic, and baker. The middle SEP category contains master craftsmen, lower white-collar workers, and small-scale entrepreneurs. This SEP is dominated by merchants, followed by engineers and teachers. Lastly, the high SEP category consists of academics, large-scale entrepreneurs, and clerics. It is most frequently represented by priests, physicians, and professors. In general, these categories are ordinal with respect to social status but most of our estimates of social mobility do not crucially rely on this feature. We exclude farmers in the main analysis, since their share is negligible in our sample (below 3 percent over the entire period). Instead, we provide results when including farmers in Appendix 2B as a robustness check.

We argue that the SEP categorization by Schüren (1989) is the most suiting one for our Zurich citizens sample as it is specifically designed for occupations in the German speaking area in the nineteenth century. In order to obtain internationally comparable results, we also categorized occupations similar to Long and Ferrie (2013), Modalsli (2017), and Pérez (2019) into farmers, a white-collar group (all non-manual workers), skilled workers (that require some education or training), and unskilled workers (requiring little to no training).[11] We call this classification the Long-Ferrie classification. First, we employed the Historical International Standard Classification of Occupations (HISCO) according to Van Leeuwen et al. (2002) that allowed to map occupations into the Historical International Social Class Scheme (HISCLASS, Van Leeuwen and Maas, 2011). We further divided HISCLASS into the four mentioned categories. Following Long and Ferrie (2013)

[10]Schüren (1989) actually provides six distinct SEPs that further divide low and middle SEP in three and two sub-groups, respectively. However, Zurich's citizenry was concentrated in the upper part of this SEP distribution. Thus, we condense the original classification into three groups.

[11]The most frequent occupations in the white-collar group are merchant, priest, and physician. Skilled workers are predominantly working as mechanics, bakers, and blacksmiths. Mercenary, upholsterer, and glazier are the most frequent occupations among unskilled workers.

and Modalsli (2017), we split the white-collar group in two (the resulting classification will be called extended Long-Ferrie categorization) to investigate the effect of the number of categories on our results. We provide a detailed description on how we classified occupations and the results excluding and including farmers in Appendix 2B. Qualitatively, our results of the main analysis employing the SEP categorization and the robustness checks employing the Long-Ferrie categorizations are in line.

Figure 2.2 displays the occupational distribution across the three SEPs among Zurich citizens belonging to families that held Zurich citizenship already before 1820 (henceforth: C1820 families or C1820 sample) over time. We observe that middle SEP occupations became more frequent while there was a reduction in both the share of individuals in low and high SEP occupations. This concentration towards middle SEP is in line with the structural changes related to the industrialization in Zurich (Section 2.1). Figure 2B.1 in Appendix 2B shows that the structural changes can be observed with the Long-Ferrie categorization in a similar way. We see a strong increase in the share of white-collar occupations concentrated in the lower white-collar category. The share of manual workers is comparatively small and decreasing over time. Note that the number of observations is slightly decreasing because we include all families holding Zurich citizenship already before 1820. Consequently, we exclude families naturalized thereafter. Similarly, we miss all daughters reducing the sample population in spite the overall population growth. Again, this procedure homogenizes the sample improving the comparability across time (Clark, 2014, p. 108–113). In the next section, we want to examine how intergenerational mobility changed over time, so we switch the focus from the cross-section of citizens to the father-son pairs contained in the data.

2.3 Results

Absolute Mobility We start our analysis of the level of social mobility of Zurich's citizenry with a measure of absolute mobility.[12] Measures of absolute mobility describe what people actually experienced given the changes in the social structure. Thus, they do not account for the structural changes described in Sections 2.1 and 2.2. The most important of these measures is the transition matrix with dimensions according to the number of occupational categories NxN (in our case 3x3). The transition matrix shows

[12] In this entire section, we follow the structure of Modalsli (2017) closely.

absolute frequencies X_{ij} of achieving a specific occupational category j conditional on the father's category i, with $i, j \in \{1, ..., N\}$ indexing the three categories low, middle, and high SEP. The transition matrices by year of observation are displayed in Table 2A.1 in Appendix 2A. Note that we quantify social mobility between 1819 and 1879 throughout the paper. We restrict the analysis to this period for two reasons. First, the data collection is still ongoing for the years before 1819. Second, we quantify social mobility by year of the father's observation. Consequently, we observe the son's occupation some decades later. Hence, the number of observations with a father-son pair (in which the son is of full age) decreases over time. Consequently, we restrict our period to 1819–1879.[13]

Based on the transition matrices, we can calculate transition probabilities p_{ij} measuring how probably a son entered category $j \in \{1, ..., N\}$ conditional on the occupational category of the father $i \in \{1, ..., N\}$. These probabilities are defined as

$$p_{ij} = \frac{X_{ij}}{\sum_{j=1}^{N} X_{ij}}, \tag{2.1}$$

where $N = 3$ and i, j index low, middle, and high SEP occupations.

Figure 2.3 shows the evolution these probabilities. First, we observe that the probabilities of remaining in the same occupational category as the father were large over the entire period. The probabilities lie between 51 and 62 percent for low SEP occupations, between 52 and 68 percent for middle SEP, and between 35 and 43 percent for high SEP. The intergenerational persistence in SEP is least pronounced for high SEP occupations which can be partially explained by the small fraction of occupations in this category (around 20 percent). Second, the transition probabilities between the two tailing SEPs (low and high) are comparatively small and decreasing over time. The probability for the son of a low (high) SEP father to enter a high (low) SEP occupation decreased from 12 (26) to 7 (14) percent. Third, Figure 2.3 shows that the probability of a son entering a middle SEP occupation increased irrespective of the father's occupation. The transition probabilities increased from 25, 52, and 37 percent to 37, 68, and 44 percent for sons of low, middle, and high SEP fathers, respectively. This is closely linked to more middle SEP occupations becoming available over the course of the century as shown in Figure 2.2. The evidence on changes in absolute mobility over time is mixed. While absolute mobility increased for low SEP occupations, it decreased for middle and high SEP occupations.

[13] Further, note that fathers show up multiply in the transition matrix if they have more than one son.

To control estimates of social mobility for structural changes in the economy, one has to apply measures of relative mobility.

Relative Mobility Our second approach to measuring intergenerational mobility is based on measures of relative mobility. These measures allow to account for changes in the occupational structure to put more emphasis on the (in)equality of chances. The easiest method to display relative mobility are two-way log-odds ratios. Following Modalsli (2017), there are two steps to arrive at two-way log-odds ratios starting from transition probabilities. First, one has to quantify the "advantage" the son of a father with occupational category i has to enter the same category as compared to all other categories. This "advantage" is given by the transition probability ratio $p_{ii}/(1-p_{ii})$. The "advantage" measure is still affected by structural changes in the economy as the probability to enter an occupational category is affected by the relative size of the respective category. Second, one has to compare $p_{ii}/(1-p_{ii})$ to the "advantage" for occupational category i for sons of fathers in any other category $\neg i$, given by $p_{\neg ii}/(1-p_{\neg ii})$. The ratio of the two "advantage" measures yields an odds ratio. Taking logs of this odds ratio results in the two-way log-odds ratio for category i given by

$$\Theta_{2,i} = log\left[\frac{p_{ii}/(1-p_{ii})}{p_{\neg ii}/(1-p_{\neg ii})}\right]. \tag{2.2}$$

The resulting two-way log-odds ratios tell how much more likely the son of a father with occupational category i is to enter category i rather than any other category as compared to the son of a father with different occupational category $\neg i$. This log-odds ratio would be equal to zero if the probability of the son to enter category i is independent of the father's occupation.

Figure 2.4 depicts the two-way log-odds ratios for the three SEPs over the entire period. The figure displays that the log-odds ratios of all occupational categories increased over time. Even though low SEP occupations exhibit increasing absolute mobility, they are subject to the most pronounced decrease in relative mobility as measured by the two-way log-odds ratio. The son of a low SEP father (classified in 1819) was approximately $e^{1.54} = 4.7$ times more likely to enter a low SEP occupation compared to other occupations than the son of a middle or high SEP father. This ratio increased to approximately 8 by 1879. Moreover, low SEP occupations did not only exhibit the largest increase in immobility but were the least mobile over the entire period, while middle SEP occupations were the most mobile and exhibited the least pronounced increase (the odds ratio increased from 2.5 to 3.0). Overall, the log-odds ratios draw a picture of decreasing intergenerational mobility for Zurich's citizenry with increasing persistence of low SEP being the main driver.

The two-way log-odds ratios display relative mobility and thus allow to correct for structural changes in the occupational distribution. However, they merely emphasize the diagonal of the transition matrix. Consequently, one has to employ a different measure to obtain a more comprehensive description of relative social mobility. Such a measure has to aggregate all possible log-odds ratios $\Theta_{ijlm} = log\left[\frac{p_{ij}/p_{im}}{p_{lj}/p_{lm}}\right]$ for any two occupation categories of the father i and l and any two categories of the son j and m.[14] The Altham statistic introduced by Altham (1970a,b) is such a metric that has been employed in the recent occupational mobility literature (e.g. Altham and Ferrie, 2007; Long and Ferrie, 2013; Modalsli, 2015, 2017; Boberg-Fazlić and Sharp, 2018; Pérez, 2019).[15] The statistic quantifies the total distance between two transition matrices P and Q by calculating the quadratic mean of all differences in the log-odds ratios between the two matrices. The Altham statistic for any two NxN matrices P and Q with log-odds ratios Θ^P_{ijlm} and Θ^Q_{ijlm} is defined as

$$d(P,Q) = \left[\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}\sum_{m=1}^{N}(\Theta^P_{ijlm} - \Theta^Q_{ijlm})^2\right]^{1/2}. \tag{2.3}$$

To quantify the distance of a transition matrix P to perfect mobility, one has to compare P to a matrix of ones J (representing perfect mobility). All log-odds ratios of J are equal to zero as rows and columns are independent. Consequently, the Altham statistic for the comparison of P with J to quantify the extent of immobility becomes

$$d(P,J) = \left[\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}\sum_{m=1}^{N}(\Theta^P_{ijlm})^2\right]^{1/2}. \tag{2.4}$$

[14] This log-odds ratio quantifies the odds that a son enters category j rather than m, given that the father's occupation belonged to category i respectively l. If the occupational outcome of the son is independent of the father's occupation these log-odds ratios are equal to zero.

[15] Powers and Xie (2000, p. 95–99) and Agresti (2002, p. 43–47) provide theoretical background on the Altham statistic.

The first column of Table 2.1 contains the Altham statistic $d(P, J)$ comparing each year's transition matrix with perfect mobility. The G^2-test proposed by Altham and Ferrie (2007) reveals that the Altham statistics are significantly different from zero on the 0.1 percent level in all years. The strong increase in the Altham statistic confirms the impression from Figure 2.4 of decreasing mobility over the nineteenth century. Complementary to the change in the level of mobility, we investigate how quickly the structure of social mobility changed. Namely, we provide an Altham statistic comparing each year's transition matrix with the one from 1819 (second column of Table 2.1). We observe that the structure of mobility started to differ around the 30s and 40s.[16] We do not observe large jumps in the value of this Altham statistic, which might have indicated a structural break. Thus, the decrease in relative mobility appears to have been a more continuous process.

We provide alternate measures of mobility in the other columns of Table 2.1. First, we display the share of mobile individuals M representing the off-diagonal of the transition matrices being a measure of absolute mobility. The fraction of mobile individuals was comparatively small as only 48 (42) percent of sons entered a different occupational category than their father exhibited in 1819 (1879).[17] We still observe that mobility decreased over time but in a less monotone manner. The decrease in absolute mobility as represented by M seems to be concentrated in the second half of the analyzed period. To correct the fraction of mobile individuals, we follow Altham and Ferrie (2007) to calculate M'. M' is the share of individuals not entering the same occupational category as their father when the transition matrices are adjusted to have the same marginal frequencies as the transition matrix in 1819. Hence, M' should display relative mobility. The drop in occupational mobility is similar to the one estimated when employing M but exhibits a more continuous reduction in mobility. Second, U, D, U', and D' are the only measures of mobility that depend on the interpretation of low, middle, and high SEP occupations being sorted according to their socioeconomic status (ordinal interpretation of SEP). They split M and M' into upward and downward mobile individuals. If for

[16] Keep in mind that the measurement year of our mobility estimates are defined by the year of observation of the father's occupation.

[17] As a comparison, Falcon (2016) finds that between 50 and 60 percent of Swiss men were socially mobile during the twentieth century. Her categorization of occupations is better comparable to our extended Long-Ferrie categorization exhibiting between 52 and 56 percent mobile individuals (see Table 2B.1). This provides suggestive evidence of small differences between the levels of mobility in the two centuries. Still, the numbers are only roughly comparable.

example a middle SEP father has a son that enters an occupation with high SEP this is categorized as upward mobility. Interestingly, U exhibits an inverse u-shape implying that upward mobility became more likely before dropping a little below the initial level. This inverse u-shape vanishes if one corrects for structural changes as shown by the drop in U'. This is in line with middle SEP becoming more prevalent while the share of low SEP occupations dropped strongly. This structural change featuring transition out of low SEP occupations into middle SEP occupations shows up in U but leaves U' unaffected. D and D' both decreased continuously. Jointly, one can conclude that the drop in absolute mobility (M) was mostly concentrated in a reduction of downward mobility (D), while the reduction in relative mobility (M') seems to exhibit a more balanced reduction in upward and downward mobility.

All of the measures provided so far have addressed life-cycle bias for sons to some extent.[18] However, we did not control for differences in the age of the father in the year his occupation is classified. Thus, one concern is that the observed changes might be affected by a changing age structure in the sample. To tackle this issue, we follow Modalsli (2015) who provides a means to estimate log-odds ratios with controls: one can employ a multinomial logit model (see e.g. Agresti, 2002, p. 268) to get controlled log-odds ratios. Closely following the notation of Modalsli (2015) and Modalsli (2017), let us denote the occupational outcome of son s in the father-son pair q by o_q^s. $\mathbf{D_q} = \{D_1, ..., D_N\}$ is a set of dummies indexing the corresponding father's occupation if there are N different occupational classes. Let $\mathbf{X_q}$ denote a vector of individual control variables (e.g. age). Then one can estimate a system of $N-1$ equations (indexed by k) for son's occupation

$$log\left[\frac{Pr(o_q^s = k)}{Pr(o_q^s = 1)}\right] = \alpha_k + \beta_k'\mathbf{D_q} + \gamma_k'\mathbf{X_q} + \epsilon_{k,q}, \qquad k = 2, 3, ..., N, \tag{2.5}$$

where α_k is the estimated constant, γ_k' are the coefficients of the controls, and $\beta_k' = \{\beta_k^1, ..., \beta_k^{N-1}\}$ is the parameter vector of interest. Using the β coefficients allows to calculate the Altham statistic (for a comparison with perfect mobility represented by J)

[18] As mentioned in Section 2.2, we classified sons' occupations as close to their 40th birthday as possible and excluded sons older than 65 or younger than 20 in the corresponding year.

by

$$d(P,J) = \left[\sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{l=1}^{N} \sum_{m=1}^{N} \{(\beta_j^i - \beta_m^i) - (\beta_j^l - \beta_m^l)\}^2 \right]^{1/2} . \tag{2.6}$$

We employ this controlled Altham statistic to account for age differences of both fathers and sons. Specifically, we estimate the system of equations given in equation (2.5) with controls for a quadratic function of son's age and father's age. The resulting estimates for the controlled Altham statistic are provided in Figure 2.5. The point estimates of the controlled Altham statistics are higher and increase marginally less pronounced (from 7.4 to 10.9) as compared to the uncontrolled statistic. We still find that our result of decreasing intergenerational mobility is robust to controlling for differences in the age at classification.

Correlation Coefficient Many studies on intergenerational mobility rely on income rather than occupation data (Black and Devereux, 2011). The use of income data does not only allow for estimates of intergenerational earnings elasticities but also for estimates of an income correlation coefficient. Moreover, Clark (2014), Clark and Cummins (2014, 2015), and Clark et al. (2015) provide correlation coefficients for elite status. The advantage of correlation coefficients is their simplicity with respect to interpretability. Further, the square of the correlation coefficient displays how much of the variation across the underlying measure among sons can be explained by its variation among fathers (Clark, 2014).

In order to get estimates that allow for similar interpretations, we cannot rely on income data nor elite status among rare surnames. Instead, we provide a standardized measure based on the Historical Cambridge social interaction and stratification scales (HISCAM, Lambert et al., 2013) that allow us to estimate a correlation coefficient.[19] After categorizing all occupations according to HISCO (Van Leeuwen et al., 2002), we are able to employ the linked HISCAM measure of occupational stratification, ranking occupations in a continuous way on a scale from zero to one hundred. In order to arrive at an estimate of an intergenerational correlation coefficient, we have to standardize this measure in every observation year. Namely, we replace the original HISCAM values for

[19]Note that comparing correlation coefficients of different measures is merely illustrative and does not allow for too detailed interpretations.

both the father f and the son s in the father-son pair q where the father is observed in year t by

$$HISCAM^{std}_{qtk} = \frac{HISCAM_{qtk} - \overline{HISCAM_{tk}}}{\sigma(HISCAM_{tk})}, \qquad k \in \{s, f\}, \tag{2.7}$$

where $\overline{HISCAM_{tk}}$ is the average HISCAM value among all k in the set of father-son pairs observed in year t and $\sigma(HISCAM_{tk})$ is the corresponding standard deviation of the HISCAM value among k. The resulting standardized value of HISCAM has zero mean and a standard deviation of one. Following Clark (2014), this enables us to get the correlation coefficient β_t for year t directly out of the regression

$$HISCAM^{std}_{qts} = \beta_t HISCAM^{std}_{qtf} + \varepsilon_{qt}, \qquad t = 1819, 1821, ..., 1879. \tag{2.8}$$

Figure 2.6 contains our estimates of the correlation coefficient. We find predominantly insignificant fluctuations in the correlation coefficient over time. Similar to the share of mobile M, we find a slight but insignificant increase in social mobility in the first part of the period followed by a decrease until the end of our observation period. The values lie between 0.29 and 0.40 suggesting that between 9 and 16 percent of the variation across standardized HISCAM measures among sons can be explained by the variation in the fathers' scores. A comparison with income or education correlation coefficients does not yield conclusive evidence on the relative level of mobility. However, we find that our estimates are roughly comparable in size to recent estimates for earnings and education correlation for several countries (e.g. Black and Devereux, 2011; Vosters and Nybom, 2017; Adermon et al., 2018; Torche and Corvalan, 2018; Vosters, 2018). Hence, we find significantly lower levels of correlation than Clark (2014) as well. To wrap up, all of the measures employed above agree with respect to a decreasing level of mobility in the second half of the observed period.

Robustness and International Comparison Appendix 2B explores whether our results are affected by the our choice of the occupational categorization according to SEP. We employ the Long-Ferrie categorization described in Section 2.2 and Appendix 2B with distinction between white-collar occupations, skilled, and unskilled manual work. To investigate whether the number of categories affects our results, we follow Long and

Ferrie (2013) and Modalsli (2017) and further split the white-collar group into a lower and a higher managers group. We find that our results are not driven by the specific categorization employed to measuring mobility. Including farmers, does not change the results qualitatively either. We observe decreasing levels of absolute and relative mobility in Zurich's citizenry over the course of the nineteenth century across all occupational categorizations.

In Appendix 2C, we shift the focus of the analysis away from our homogeneous C1820 sample including only citizen-families that held Zurich citizenship already before 1820. Instead, we combine our data on citizens who lived in the city of Zurich with the available data on registered residents to generate a census sample that should be able to reflect the level of social mobility in the city of Zurich. Note that we are not able to reconstruct the entire resident population of Zurich as we do not have information on foreign temporary residents. Moreover, the information on father-son pairs in the pool of registered residents is sparser. Hence, these results have to be taken with caution but should give some insight in how mobility has evolved in the city of Zurich for the largest part of the population.[20]

We find that, mobility decreased less in our census sample than in our C1820 sample. When we include farmers in the census analysis, however, we find a strong decrease in immobility similar in magnitude to the cross-country difference in mobility between the United States and the United Kingdom or Norway around the late nineteenth century (Long and Ferrie, 2013; Modalsli, 2017). Excluding farmers, we find that mobility decreased until mid-century. Thereafter, it stagnated.[21]

Summarizing, we find that both absolute and relative mobility decreased significantly among Zurich citizens between 1819 and 1879. Our results show increasing intergenerational persistence across all socioeconomic positions. This increase is most pronounced for occupations in the low SEP category. Our results are robust to a variety of extensions.

2.4 Conclusion

Nineteenth century Zurich was subject to important structural change. This change encompassed institutional advances on federal, cantonal, and municipal level, unprecedented

[20]In 1889, the number of citizens and registered residents was 21,961 comparing to 6,961 temporary foreign residents including women and children (Schulthess and Meister, 1889). Thus, we lack information on roughly 24 percent of the total population.

[21]For details, see Appendix 2C.

population growth, industrialization, the development of the banking sector, the foundation of the universities, and the development of a railway system with Zurich as one of its hubs. We observe the changes in the labor market structure in our data featuring a transition towards middle socioeconomic position (lower white-collar occupations). Consequently, one might expect social mobility to be increasing during this time period for two reasons. On the one hand, industrialization generated new opportunities and rendered certain occupations obsolete (Kury, 2012). On the other hand, the political climate was marked by a progressive democratization leading to a break of power among conservative forces (Behrens, 2015; Illi and König, 2017).

Despite this expectation of increasing mobility, we find a decreasing level of both absolute and relative mobility for Zurich citizens between 1819 and 1879. We provide first evidence that this result prevails for the resident population of the city of Zurich. Upward and downward mobility were about equal but downward mobility decreased more strongly. We find that the intergenerational persistence was largest for low SEP occupations. These occupations also exhibited the largest increase in persistence over the course of the century. Potential candidates to explain this persistence are a poverty-trap mechanism, labor-market imperfections due to guild regulations, or an inheritance mechanism specific to low socioeconomic positions. Further, mid-century estimates suggest that the level of social mobility in Zurich was comparable to the one in the United States in the late nineteenth century. After the mentioned decrease in intergenerational mobility, Zurich exhibited a similar level of mobility as Norway or the United Kingdom by the end of the nineteenth century.

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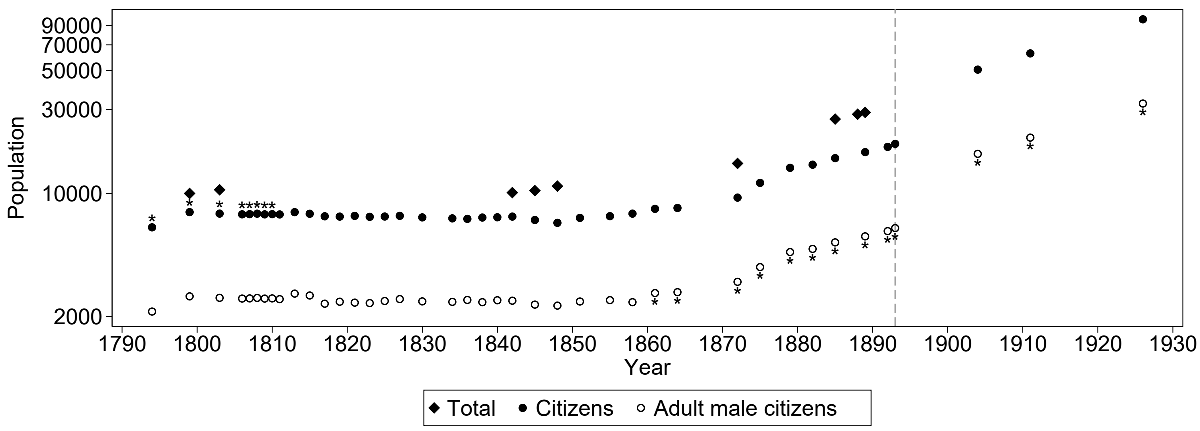
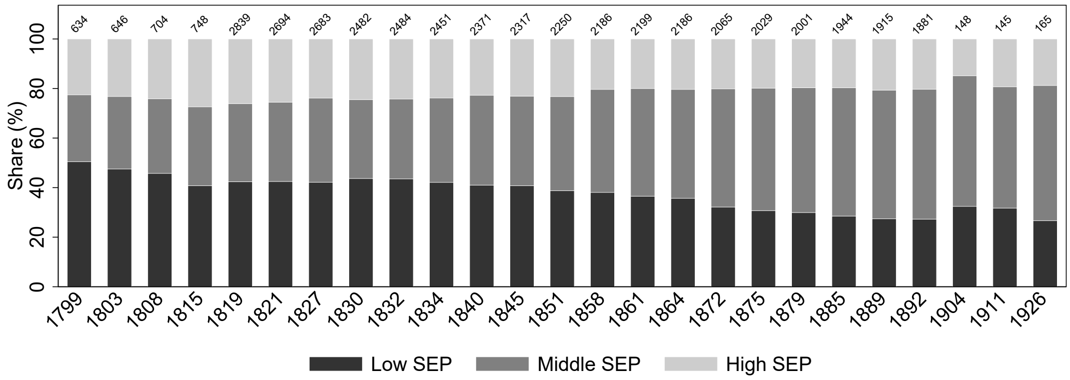
Figures and Tables

Figure 2.1. Population and citizenry of Zurich.



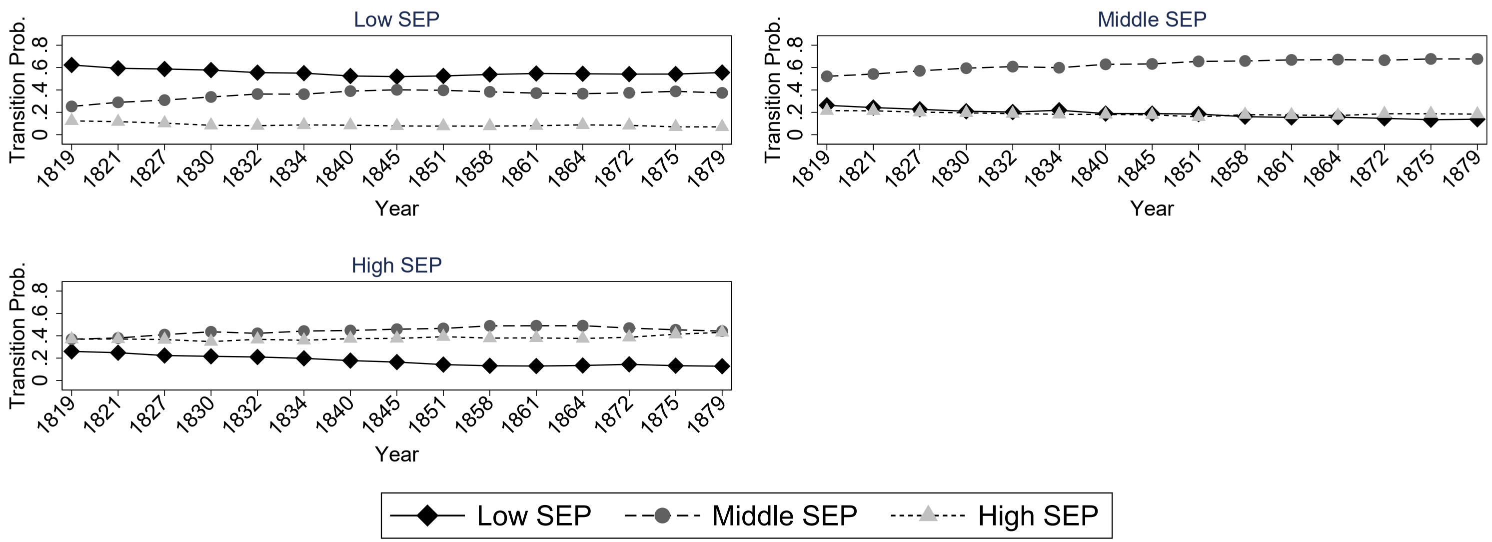
Note: *Citizens* include women and children. *Adult male citizens* is close to our C1820 sample but also includes individuals naturalized after 1820. The stars denote inferred values. The dashed line marks the incorporation of surrounding municipalities into Zurich in 1893. Note that citizens do not necessarily live in the city of Zurich. The numbers originate from aggregate statistics contained in the directory of citizens.

Figure 2.2. Occupational structure over time.



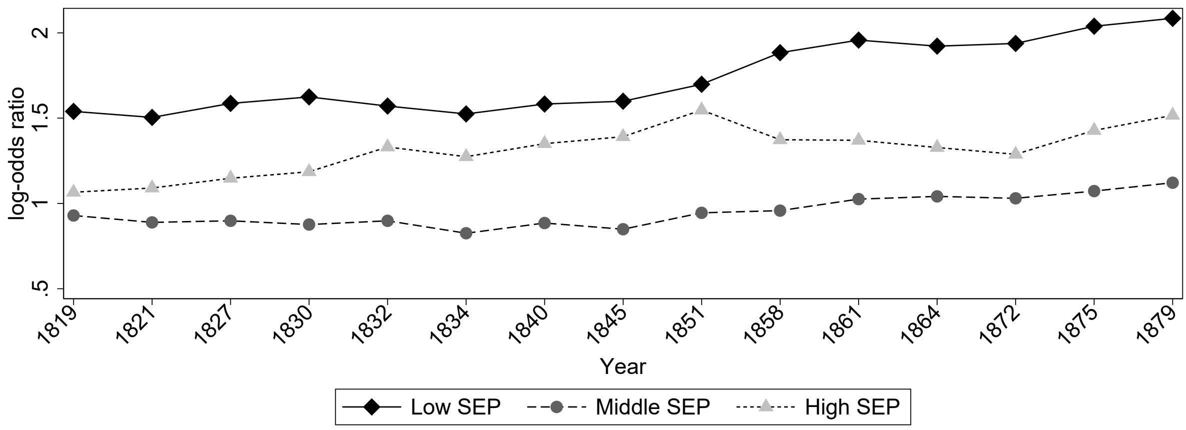
Note: This figure includes every citizen belonging to families that held Zurich citizenship before 1820. The numbers above the columns denote the number of observations per year. The data before 1819 and after 1892 are not yet completely digitized.

Figure 2.3. Transition probabilities over time.



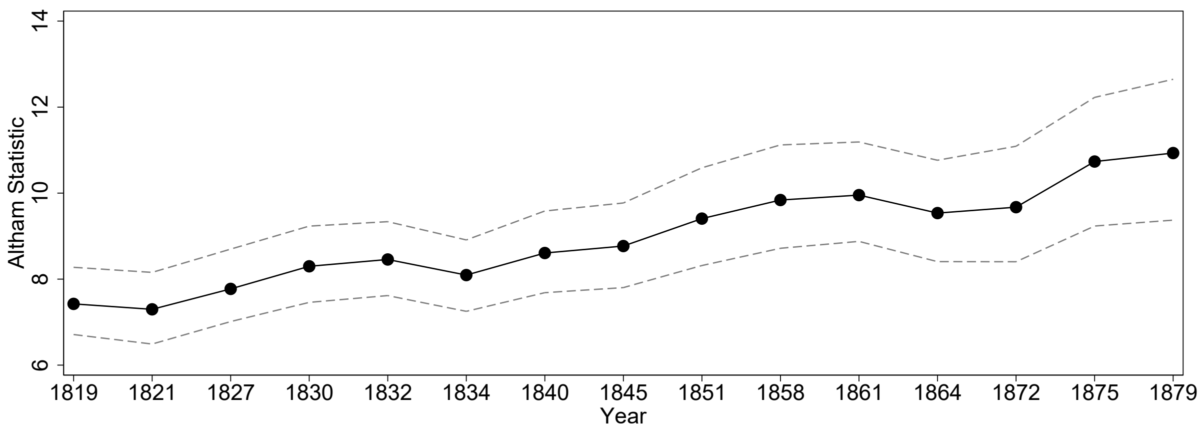
Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father. For example, the upper-left panel displays the transition probabilities of sons whose fathers had a low SEP occupation in the corresponding year.

Figure 2.4. Log-odds ratios over time.



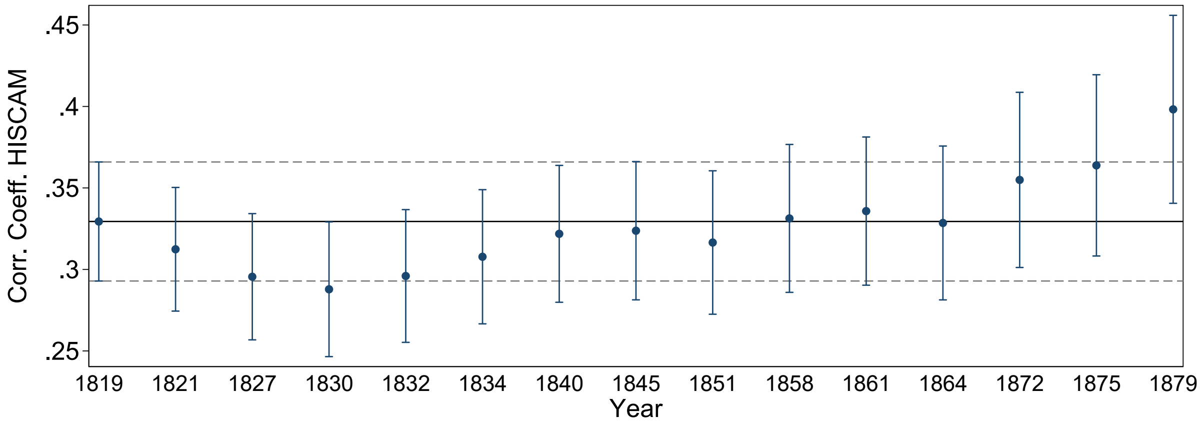
Note: These are the two-way log-odds ratios $\Theta_{2,i}$, with $i \in \{1, 2, 3\}$ representing the three SEPs (low, middle, and high). One can read this graph as follows: the son of a father with a low SEP occupation in 1819 was approximately $e^{1.54} = 4.7$ times more likely to enter a low SEP occupation compared to middle or high SEP occupations than the son of a father with a middle or high SEP occupation.

Figure 2.5. Altham statistic controlled for age and age squared of both the son and father over time.



Note: This is the Altham statistic controlled for a quadratic function of father's and son's age following Modalsli (2015). The confidence intervals are calculated by the same bootstrap technique as presented in Modalsli (2015, p. 8).

Figure 2.6. Correlation coefficient of the standardized HISCAM measure over time.



Note: The solid (dashed) black line represents our estimate (confidence intervals) for the year 1819. How we arrive at this correlation coefficient is explained in Section 2.3.

Table 2.1. Measures of mobility over time.

Year	AS	AS1819	M	U	D	M'	U'	D'
1819	6.84***	0.00	48.06	21.81	26.25	48.06	21.81	26.25
1821	6.94***	0.58	48.47	22.61	25.86	48.19	22.10	26.09
1827	7.47***	1.00	47.53	22.45	25.07	47.36	21.67	25.69
1830	7.96***	1.77	47.77	22.48	25.29	47.06	21.77	25.29
1832	8.20***	2.19*	47.55	23.40	24.14	46.65	21.68	24.97
1834	7.84***	1.80	48.04	23.23	24.81	47.41	21.73	25.68
1840	8.30***	2.19*	46.92	24.85	22.07	46.42	21.37	25.05
1845	8.64***	2.62**	47.07	24.43	22.64	46.20	21.17	25.02
1851	9.24***	3.08***	45.60	23.31	22.28	44.50	20.03	24.48
1858	9.56***	3.16***	44.68	23.38	21.29	44.02	19.82	24.20
1861	9.66***	3.13***	43.73	22.69	21.04	43.31	19.42	23.90
1864	9.28***	2.66**	43.67	22.09	21.58	43.54	19.45	24.10
1872	9.42***	2.86*	43.48	22.21	21.26	43.56	19.84	23.72
1875	10.42***	4.00***	42.39	21.68	20.71	42.09	19.27	22.82
1879	10.69***	4.23***	41.70	20.94	20.76	41.29	18.72	22.57

Note: The mobility measures (based on SEP) are: (AS) conventional Altham statistic $d(P, J)$ showing distance from perfect mobility, (AS1819) Altham statistic comparing each year's transition matrix with the one from 1819 to show structural mobility changes, (M) share of off-diagonal/share of mobile, (U) share of upward mobile, (D) share of downward mobile, (M') share of off-diagonal with marginal distribution adjusted to the transition matrix of 1819, (U') share of upward mobile with marginal distribution adjusted to 1819, and (D') share of downward mobile with marginal distribution adjusted to 1819. The stars indicate significance levels from the G^2-test (*: 5 %, **: 1 %, ***: 0.1 %). Degrees of freedom: 4.

Appendix

2A Transition Matrices

This Appendix contains all transition matrices referred to in Section 2.3.

TABLE 2A.1. TRANSITION MATRICES OF SEP.

(A). 1819.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	705	283	210	1,198
middle SEP (M)	286	562	298	1,146
high SEP (H)	140	231	298	669
Row sum	1,131	1,076	806	3,013

(B). 1821.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	570	237	177	984
middle SEP (M)	278	530	271	1,079
high SEP (H)	112	209	265	586
Row sum	960	976	713	2,649

(C). 1827.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	553	238	152	943
middle SEP (M)	291	598	279	1,168
high SEP (H)	97	211	249	557
Row sum	941	1,047	680	2,668

(D). 1830.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	507	187	141	835
middle SEP (M)	296	530	284	1,110
high SEP (H)	74	174	227	475
Row sum	877	891	652	2,420

(E). 1832.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	508	178	137	823
middle SEP (M)	333	534	275	1,142
high SEP (H)	74	165	240	479
Row sum	915	877	652	2,444

(F). 1834.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	480	199	123	802
middle SEP (M)	316	545	274	1,135
high SEP (H)	76	166	223	465
Row sum	872	910	620	2,402

(G). 1840.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	451	171	96	718
middle SEP (M)	335	569	241	1,145
high SEP (H)	73	164	202	439
Row sum	859	904	539	2,302

(H). 1845.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	422	166	90	678
middle SEP (M)	326	557	251	1,134
high SEP (H)	64	157	206	427
Row sum	812	880	547	2,239

(I). 1851.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	402	156	75	633
middle SEP (M)	304	554	245	1,103
high SEP (H)	59	135	206	400
Row sum	765	845	526	2,136

(J). 1858.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	361	135	60	556
middle SEP (M)	257	552	223	1,032
high SEP (H)	52	150	173	375
Row sum	670	837	456	1,963

(K). 1861.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	340	128	56	524
middle SEP (M)	231	554	212	997
high SEP (H)	50	146	165	361
Row sum	621	828	433	1,882

(L). 1864.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	303	126	55	484
middle SEP (M)	204	540	201	945
high SEP (H)	49	138	154	341
Row sum	556	804	410	1,770

(M). 1872.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	214	95	46	355
middle SEP (M)	148	434	149	731
high SEP (H)	33	122	123	278
Row sum	395	651	318	1,364

(N). 1875.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	186	80	40	306
middle SEP (M)	133	404	137	674
high SEP (H)	24	112	125	261
Row sum	343	596	302	1,241

(O). 1879.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	168	73	35	276
middle SEP (M)	113	357	121	591
high SEP (H)	21	97	118	236
Row sum	302	527	274	1,103

Note: These are the transition matrices of the C1820 sample by observation year of the father. Sons' occupations are categorized around the age of forty.

2B Long-Ferrie Categorization

In this Appendix, we provide the results of our analysis with the Long-Ferrie categorizations instead of the SEP categorization. We still investigate intergenerational mobility among citizens of Zurich families that already held the citizenship before 1820 (C1820 sample). This Appendix serves both as a robustness check for the main analysis and an addition that enhances international comparability. We find that the results of the main part of the paper are robust to these alternate categorizations.

Construction of Classifications The Long-Ferrie categorization distinguishes between farmers, white-collar occupations, skilled manual workers, and unskilled workers. To construct the occupational categories we employ the HISCLASS (Van Leeuwen and Maas, 2011) classification scheme and divide its classes into the four categories. We collapsed HISCLASS 1–5 into the white-collar group, HISCLASS 6–7 into skilled workers, and HISCLASS 9–12 into lower-skilled/unskilled workers. HISCLASS 8 contains farmers. To investigate whether the number of categories affects our results, we follow Long and Ferrie (2013) and Modalsli (2017) and further split the white-collar group into a lower and higher white-collar group (for simplicity called lower and higher managers). Higher managers consist of HISCLASS 1-2 and lower managers of HISCLASS 3–5. The most frequent occupations in the higher managers group are priest, physician, and engineer. The lower white-collar group is dominated by merchants followed by shop clerks and innkeepers.

Absolute Mobility Figures 2B.2 and 2B.3 show that the observed changes in absolute mobility from Section 2.3 with the SEP classification are mirrored in the Long-Ferrie categorizations. The corresponding transition matrices are displayed in Tables 2B.3 and 2B.4. Transition probabilities towards white-collar occupations increase over time from 75, 40, and 43 percent to 87, 50, and 53 percent for sons with a father in the white-collar, skilled, and unskilled workers group, respectively. This observation reflects the increase in the share of white-collar jobs due to the structural change depicted in Figure 2B.1. The increase was concentrated on lower managers occupations (see Figure 2B.3). As with the SEP classification, the change in the probabilities of entering the same occupational category as the father did not change homogeneously. They decreased for manual workers (from 47 to 40 percent for skilled and from 28 to 22 percent for unskilled workers) but exhibited the increase mentioned before among white-collar occupations. As the distribution across occupational classes is generally less even than with the SEP categories, we observe a less pronounced diagonal overall.

Relative Mobility We can explore the two-way log-odds ratios depicted in Figure 2B.4 to correct the change in mobility for the structural change in the occupational distribution. We find that all log-odds ratios in the baseline categorization increased over time. However, we see that the log-odds ratio of unskilled workers decline towards the end of the century. Compared to our main results, the odds were more evenly distributed across occupational categories. The path they followed was qualitatively the same. The extended categorization allows to distinguish the white-collar occupations. Interestingly, this split suggests a certain degree of permeability between the lower and higher managers occupations because of two observations. First, the log-odds ratio for higher white-collar occupations increased less pronounced than for white-collar occupations overall. Second, the log-odds ratio for lower managers even decreased. Jointly, these observations indicate the proximity of the two white-collar groups. Summarizing, we find similar patterns in relative mobility as measured by two-way log-odds ratios with the SEP categorization and the Long-Ferrie categorizations. The latter categorizations exhibit a slightly less homogeneous decrease in intergenerational mobility.

Table 2B.1 contains the conventional Altham statistic and complementary measures of mobility. Again, the numbers paint the familiar picture of decreasing mobility. The three-way classification displays a less pronounced decrease (first column) and a structurally insignificant difference between the transition matrices in most of the years and the one in 1819 (second column). The second observation is overturned when employing the extended categorization. Please note that the measures denoted by U, D, U', and D' are not interpretable as upward and downward mobility in the nominal Long-Ferrie specifications. We still present them for completeness but will not put emphasis on the numbers as they merely distinguish between intergenerational movements from unskilled towards (higher) white-collar occupations and those in the opposite direction. The measures of mobile individuals M (absolute) and M' (relative) pose as the largest difference to our main analysis. They still declined over time indicating decreasing absolute and relative mobility. Nevertheless, they exhibit different levels. The estimates for the baseline Long-Ferrie categorization (especially those of M) are much lower as the distribution across occupational classes is less even. In the four-way classification, they are on a higher level than the estimates based on SEP. This underlines that the level of the share of mobile individuals is highly dependent on the specific classification employed. Comparisons across categorizations should therefore be avoided. As all of the presented measures point towards decreasing intergenerational mobility, we still conclude that our main results are robust to different classifications.

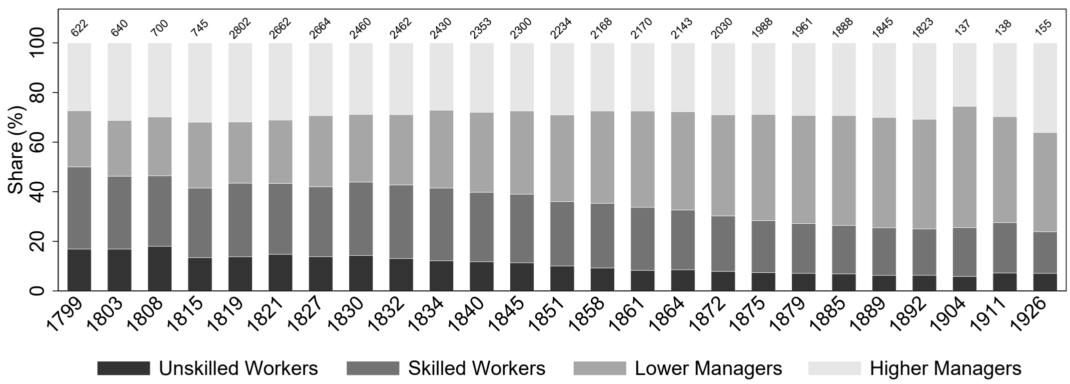
Controlling the Altham statistic for a quadratic function of age of the father and the son does not change the insights qualitatively. We still observe an increase of the statistic's point estimate in both the baseline and the extended Long-Ferrie classification as depicted in Figure 2B.5. However, the change in the three-way categorization is not statistically significant, which mirrors the insignificant Altham statistics (AS1819) in the second column of Table 2B.1. Because of the increasing point estimates and the significant increase in the extended classification's Altham statistic, we interpret the results as indication for an, at least weakly, diminishing level of social mobility.

Farmers We can extend our analysis even further by including the small fraction of farmers. The resulting conventional Altham statistics employing all occupational categorizations are summarized in Table 2B.2. We observe decreasing mobility irrespective of the categorization employed. If anything, we find a more pronounced decrease in mobility when including farmers, hinting that farming occupations might have been particularly immobile. However, we do not want to put much emphasis on farmers and their level of mobility because of the focus on a mostly urban population.[22] Bottom line, we conclude that Zurich's citizenry exhibited a significantly declining level of intergenerational mobility over the century.

Figure 2B.1. Occupational structure over time with Long-Ferrie categorization.

(a). Baseline categorization with three categories.

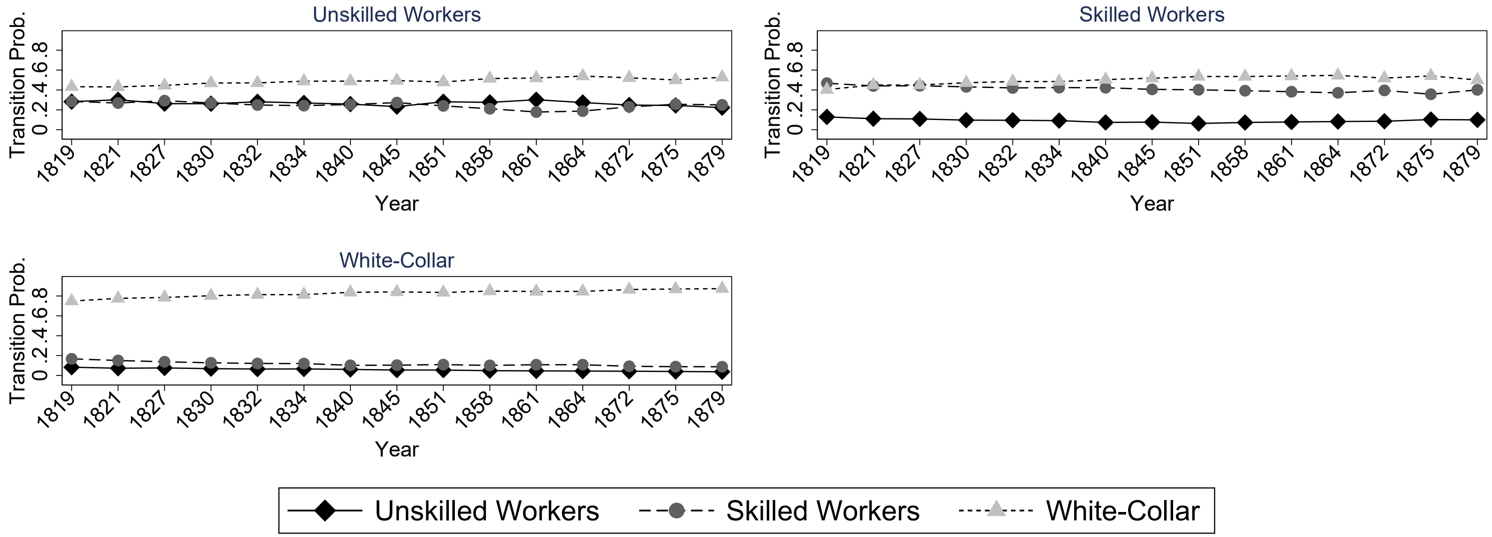
(b). Extended categorization with division of the white-collar group.



Note: These figures include every citizen belonging to families that held Zurich citizenship before 1820. The numbers above the columns denote the number of observations by year.

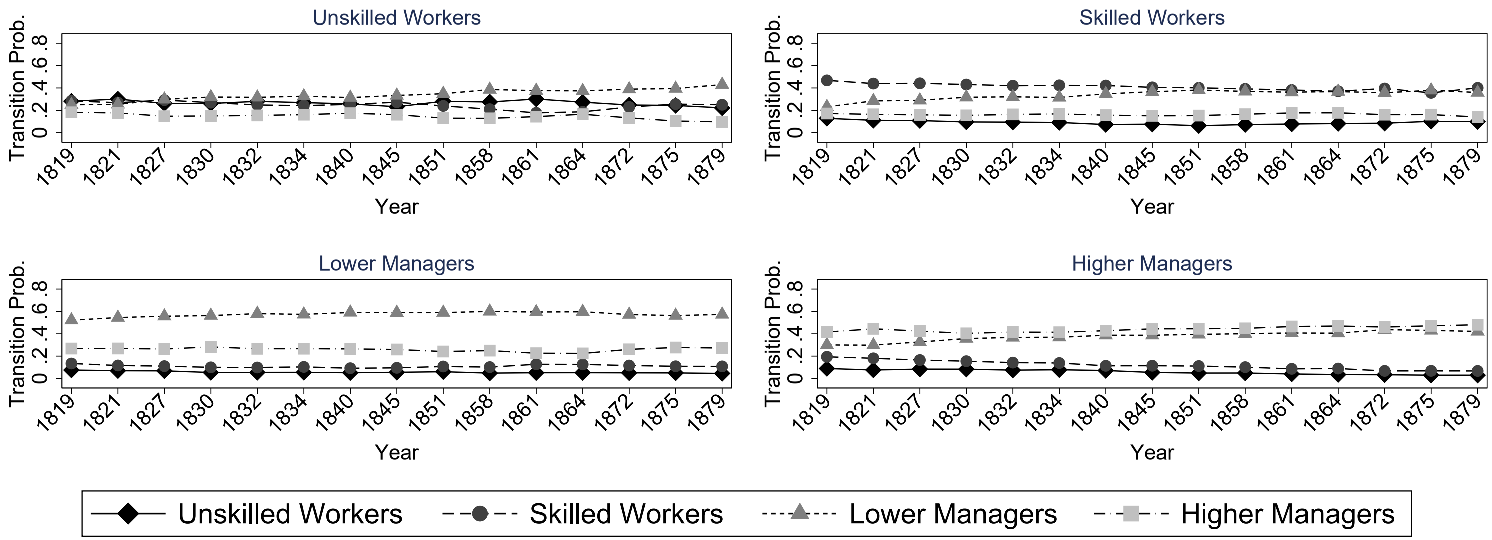
[22] Comparing these numbers to those on the United Kingdom, the United States, Norway, and Argentina reveals that Zurich's citizenry exhibited a comparable level of intergenerational mobility as Norway and the United Kingdom in the late nineteenth century, being significantly lower than the ones in the United States or Argentina (Long and Ferrie, 2013; Modalsli, 2017; Pérez, 2019).

Figure 2B.2. Transition probabilities over time with baseline Long-Ferrie categorization.



Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father. For example, the upper-left panel displays the transition probabilities of sons whose fathers were unskilled workers in the corresponding year.

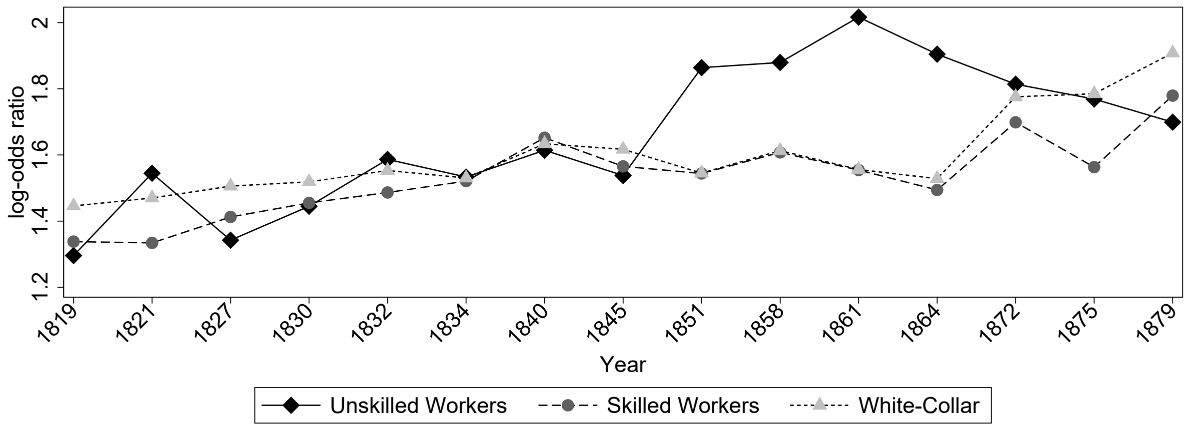
Figure 2B.3. Transition probabilities over time with extended Long-Ferrie categorization.



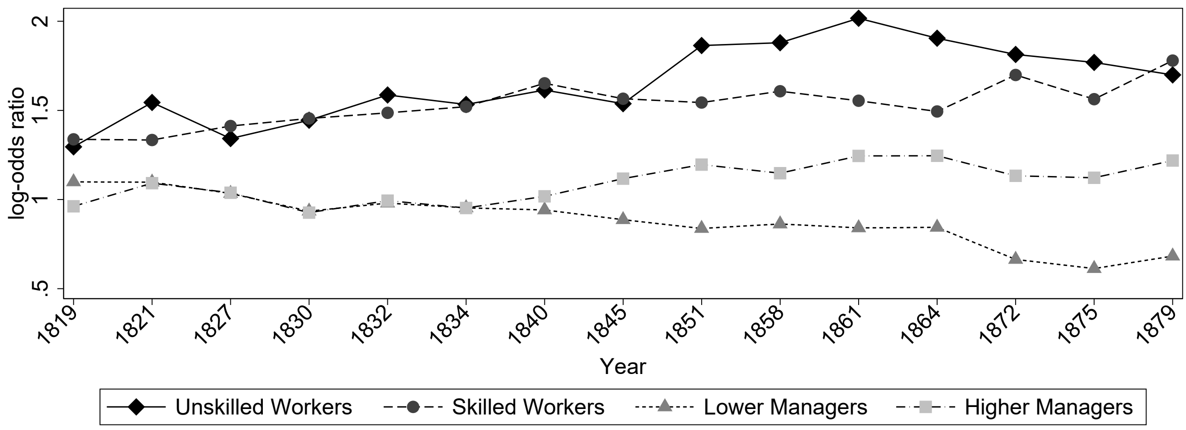
Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father.

Figure 2B.4. Log-odds ratios over time with Long-Ferrie categorization.

(a). Baseline categorization with three categories.



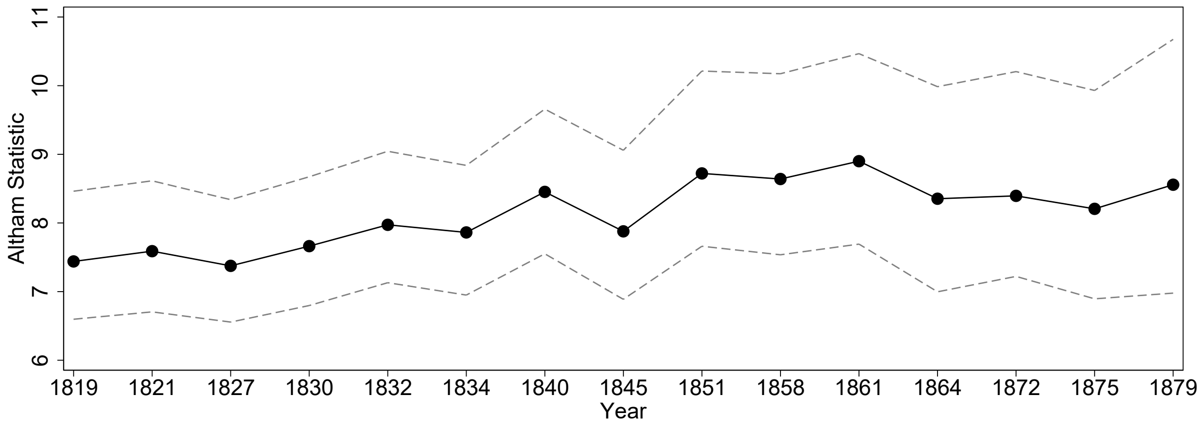
(b). Extended categorization with division of the white-collar group.



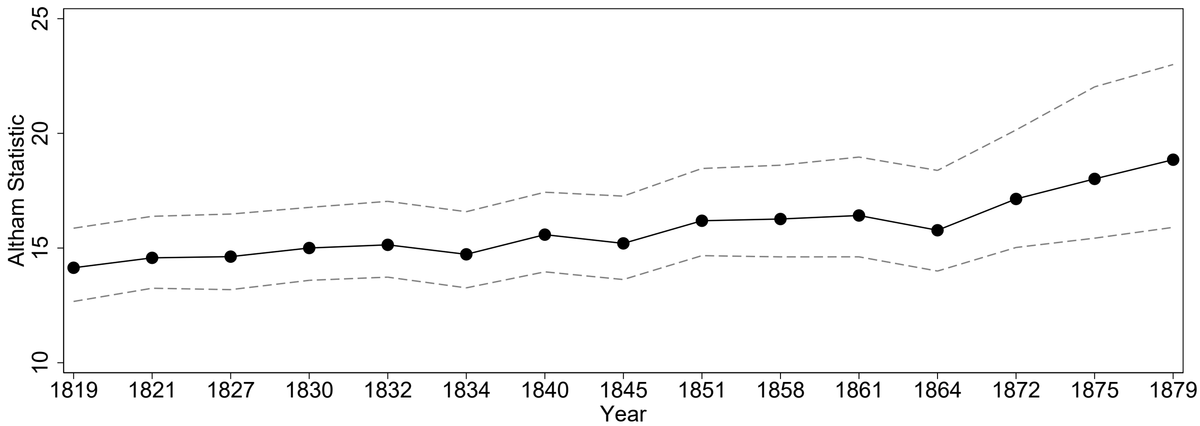
Note: These are the two-way log-odds ratios $\Theta_{2,i}$, with $i \in \{1, 2, 3(, 4)\}$ representing the three/four occupational categories (white-collar (higher and lower), skilled workers, and unskilled workers). One can read this graph as follows: the son of a father with a white-collar occupation in 1819 was approximately $e^{1.45} = 4.25$ times more likely to enter a white-collar occupation compared to non-white-collar occupations than the son of a father with a non-white-collar occupation.

Figure 2B.5. Altham statistic controlled for age and age squared of both the son and father over time with Long-Ferrie categorizations.

(a). Baseline categorization with three categories.



(b). Extended categorization with division of the white-collar group.



Note: These are the Altham statistics controlled for a quadratic function of father's and son's age following Modalsli (2015). The confidence intervals are calculated by the same bootstrap technique as presented in Modalsli (2015, p. 8).

TABLE 2B.1. MEASURES OF MOBILITY OVER TIME WITH LONG-FERRIE CATEGORIZATION.

(A). Baseline categorization with three categories.

Year	AS	AS1819	M	U	D	M’	U’	D’
1819	6.76***	0.00	38.44	19.76	18.68	38.44	19.76	18.68
1821	7.36***	1.02	37.03	20.36	16.67	37.94	19.66	18.27
1827	7.02***	0.95	35.87	19.52	16.36	37.90	19.83	18.07
1830	7.33***	1.12	35.70	20.91	14.79	37.43	19.59	17.83
1832	7.73***	1.39	35.08	21.01	14.06	36.83	19.23	17.60
1834	7.62***	1.36	34.79	20.67	14.12	36.98	19.28	17.69
1840	8.25***	2.36	32.84	20.48	12.36	35.80	19.02	16.79
1845	7.80***	1.82	32.66	20.32	12.34	36.58	19.36	17.23
1851	8.68***	2.95*	32.16	19.71	12.45	36.24	19.22	17.02
1858	8.59***	2.37	30.77	18.87	11.90	35.67	18.65	17.02
1861	8.88***	2.84	30.30	17.78	12.51	35.84	18.48	17.36
1864	8.36***	2.21	29.87	17.25	12.62	36.58	18.75	17.83
1872	8.43***	1.75	27.25	15.80	11.45	34.96	18.17	16.79
1875	8.19***	1.98	26.73	15.20	11.53	35.89	18.64	17.25
1879	8.38***	1.89	25.59	14.35	11.24	34.65	17.87	16.79

(B). Extended categorization with division of the white-collar group.

Year	AS	AS1819	M	U	D	M’	U’	D’
1819	13.07***	0.00	55.84	27.07	28.76	55.84	27.07	28.76
1821	14.13***	2.06	54.66	28.06	26.60	54.67	26.91	27.76
1827	13.90***	2.28	54.82	27.91	26.92	55.28	27.45	27.83
1830	14.38***	2.93	55.72	29.53	26.19	55.82	27.91	27.91
1832	14.63***	2.67	54.88	29.13	25.74	54.80	27.06	27.74
1834	14.17***	2.59	54.66	29.52	25.14	55.15	27.18	27.96
1840	15.06***	4.02	53.50	29.59	23.92	54.04	26.82	27.22
1845	14.92***	3.90	53.35	29.54	23.81	54.30	26.79	27.50
1851	16.00***	5.90**	53.03	28.13	24.90	53.35	26.18	27.17
1858	16.09***	5.31*	52.57	27.83	24.74	53.13	25.84	27.29
1861	16.36***	6.70***	51.87	26.18	25.69	52.59	24.60	27.99
1864	15.76***	6.20**	51.82	25.82	26.00	53.18	24.78	28.40
1872	17.05***	7.28***	52.75	25.57	27.18	53.49	25.12	28.37
1875	17.96***	8.54***	53.05	25.81	27.23	54.54	25.86	28.67
1879	18.58***	8.82***	51.65	24.55	27.10	53.08	25.19	27.89

Note: The mobility measures are: (AS) conventional Altham statistic $d(P, J)$ showing distance from perfect mobility, (AS1819) Altham statistic comparing each year’s transition matrix with the one from 1819 to show structural mobility changes, (M) share of off-diagonal/share of mobile, (U) share of upward mobile, (D) share of downward mobile, (M’) share of off-diagonal with marginal distribution adjusted to the transition matrix of 1819, (U’) share of upward mobile with marginal distribution adjusted to 1819, and (D’) share of downward mobile with marginal distribution adjusted to 1819. The stars indicate significance levels from the G^2-test (*: 5 %, **: 1 %, ***: 0.1 %). Degrees of freedom: 4 (A). and 5 (B)., respectively.

Table 2B.2. Measures of mobility over time with(out) farmers.

Year	AS(S)	AS(SF)	AS(L)	AS(LF)	AS(L+)	AS(L+F)
1819	6.84***	12.35***	6.76***	18.08***	13.07***	26.07***
1821	6.94***	11.69***	7.36***	18.56***	14.13***	27.13***
1827	7.47***	11.66***	7.02***	18.16***	13.90***	26.26***
1830	7.96***	12.47***	7.33***	18.84***	14.38***	26.77***
1832	8.20***	13.57***	7.73***	22.17***	14.63***	30.40***
1834	7.84***	13.60***	7.62***	23.21***	14.17***	31.54***
1840	8.30***	13.57***	8.25***	20.70***	15.06***	29.63***
1845	8.64***	15.68***	7.80***	20.83***	14.92***	30.50***
1851	9.24***	15.70***	8.68***	22.50***	16.00***	31.30***
1858	9.56***	17.57***	8.59***	25.30***	16.09***	34.77***
1861	9.66***	17.62***	8.88***	27.03***	16.36***	36.58***
1864	9.28***	17.04***	8.36***	26.60***	15.76***	36.04***
1872	9.42***	17.51***	8.43***	24.33***	17.05***	34.98***
1875	10.42***	17.78***	8.19***	21.80***	17.96***	34.93***
1879	10.69***	17.87***	8.38***	24.26***	18.58***	36.67***

Note: The mobility measures are: (AS(S)) conventional Altham statistic $d(P, J)$ with SEP categorization excluding farmers, (AS(SF)) conventional Altham statistic $d(P, J)$ with SEP categorization including farmers, (AS(L)) conventional Altham statistic $d(P, J)$ with baseline Long-Ferrie categorization excluding farmers, (AS(LF)) conventional Altham statistic $d(P, J)$ with baseline Long-Ferrie categorization including farmers, (AS(L+)) conventional Altham statistic $d(P, J)$ with extended Long-Ferrie categorization excluding farmers, and (AS(L+F)) conventional Altham statistic $d(P, J)$ with extended Long-Ferrie categorization including farmers. The stars indicate significance levels from the G^2-test (*: 5 %, **: 1 %, ***: 0.1 %). Degrees of freedom: 4 (L) and (S), 5 (SF), (LF), and (L+), and 6 (L+F), respectively.

Transition Matrices We present the transition matrices of the C1820 sample following the Long-Ferrie categorizations below.

Table 2B.3. Transition matrices of the baseline Long-Ferrie categorization.

(a). 1819.

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	1,346	317	161	1,824
Skilled Workers (S)	301	368	106	775
Unskilled Workers (U)	150	101	105	356
Row sum	1,797	786	372	2,955

(b). 1821.

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	1,248	292	146	1,686
Skilled Workers (S)	243	286	91	620
Unskilled Workers (U)	118	72	102	292
Row sum	1,609	650	339	2,598

(c). 1827.

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	1,320	287	136	1,743
Skilled Workers (S)	232	282	89	603
Unskilled Workers (U)	128	69	80	277
Row sum	1,680	638	305	2,623

(d). 1830.

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	1,185	289	131	1,605
Skilled Workers (S)	189	264	75	528
Unskilled Workers (U)	102	59	73	234
Row sum	1,476	612	279	2,367

(e). 1832.

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	1,211	302	131	1,644
Skilled Workers (S)	180	262	69	511
Unskilled Workers (U)	97	59	78	234
Row sum	1,488	623	278	2,389

(F). 1834.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,204	296	127	1,627
Skilled Workers (S)	178	259	63	500
Unskilled Workers (U)	98	56	70	224
Row sum	1,480	611	260	2,351

(G). 1840.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,204	289	112	1,605
Skilled Workers (S)	147	242	58	447
Unskilled Workers (U)	88	42	59	189
Row sum	1,439	573	229	2,241

(H). 1845.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,194	291	98	1,583
Skilled Workers (S)	148	228	54	430
Unskilled Workers (U)	78	43	46	167
Row sum	1,420	562	198	2,180

(I). 1851.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,153	272	92	1,517
Skilled Workers (S)	151	204	46	401
Unskilled Workers (U)	76	32	54	162
Row sum	1,380	508	192	2,080

(J). 1858.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,101	236	88	1,425
Skilled Workers (S)	132	173	36	341
Unskilled Workers (U)	63	32	47	142
Row sum	1,296	441	171	1,908

(K). 1861.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,069	222	76	1,367
Skilled Workers (S)	137	157	26	320
Unskilled Workers (U)	59	32	44	135
Row sum	1,265	411	146	1,822

(L). 1864.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,026	193	75	1,294
Skilled Workers (S)	132	131	26	289
Unskilled Workers (U)	54	29	38	121
Row sum	1,212	353	139	1,704

(M). 1872.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	832	122	59	1,013
Skilled Workers (S)	89	93	26	208
Unskilled Workers (U)	41	20	28	89
Row sum	962	235	113	1,310

(N). 1875.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	779	117	43	939
Skilled Workers (S)	80	77	22	179
Unskilled Workers (U)	36	22	21	79
Row sum	895	216	86	1,197

(O). 1879.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	695	96	38	829
Skilled Workers (S)	70	77	18	165
Unskilled Workers (U)	30	19	16	65
Row sum	795	192	72	1,059

Note: These are the transition matrices of the C1820 sample by observation year of the father. Sons' occupations are categorized around the age of forty.

Table 2B.4. Transition matrices of the extended Long-Ferrie categorization.

(a). 1819.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	412	216	135	68	831
Lower Managers (L)	298	420	182	93	993
Skilled Workers (S)	193	108	368	106	775
Unskilled Workers (U)	89	61	101	105	356
Row sum	992	805	786	372	2,955

(b). 1821.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	384	200	107	60	751
Lower Managers (L)	258	406	185	86	935
Skilled Workers (S)	156	87	286	91	620
Unskilled Workers (U)	66	52	72	102	292
Row sum	864	745	650	339	2,598

(c). 1827.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	359	220	102	45	726
Lower Managers (L)	277	464	185	91	1,017
Skilled Workers (S)	140	92	282	89	603
Unskilled Workers (U)	71	57	69	80	277
Row sum	847	833	638	305	2,623

(d). 1830.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	305	204	95	42	646
Lower Managers (L)	270	406	194	89	959
Skilled Workers (S)	117	72	264	75	528
Unskilled Workers (U)	63	39	59	73	234
Row sum	755	721	612	279	2,367

(e). 1832.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	315	194	102	43	654
Lower Managers (L)	279	423	200	88	990
Skilled Workers (S)	108	72	262	69	511
Unskilled Workers (U)	57	40	59	78	234
Row sum	759	729	623	278	2,389

(F). 1834.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	290	208	103	42	643
Lower Managers (L)	259	447	193	85	984
Skilled Workers (S)	97	81	259	63	500
Unskilled Workers (U)	55	43	56	70	224
Row sum	701	779	611	260	2,351

(G). 1840.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	286	204	90	40	620
Lower Managers (L)	259	455	199	72	985
Skilled Workers (S)	76	71	242	58	447
Unskilled Workers (U)	48	40	42	59	189
Row sum	669	770	573	229	2,241

(H). 1845.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	287	201	85	32	605
Lower Managers (L)	250	456	206	66	978
Skilled Workers (S)	74	74	228	54	430
Unskilled Workers (U)	35	43	43	46	167
Row sum	646	774	562	198	2,180

(I). 1851.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	292	175	78	25	570
Lower Managers (L)	259	427	194	67	947
Skilled Workers (S)	73	78	204	46	401
Unskilled Workers (U)	32	44	32	54	162
Row sum	656	724	508	192	2,080

(J). 1858.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	274	171	73	22	540
Lower Managers (L)	245	411	163	66	885
Skilled Workers (S)	62	70	173	36	341
Unskilled Workers (U)	30	33	32	47	142
Row sum	611	685	441	171	1,908

(K). 1861.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	274	153	73	21	521
Lower Managers (L)	240	402	149	55	846
Skilled Workers (S)	51	86	157	26	320
Unskilled Workers (U)	24	35	32	44	135
Row sum	589	676	411	146	1,822

(L). 1864.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	264	146	63	23	496
Lower Managers (L)	228	388	130	52	798
Skilled Workers (S)	50	82	131	26	289
Unskilled Workers (U)	20	34	29	38	121
Row sum	562	650	353	139	1,704

(M). 1872.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	217	128	38	15	398
Lower Managers (L)	206	281	84	44	615
Skilled Workers (S)	32	57	93	26	208
Unskilled Workers (U)	16	25	20	28	89
Row sum	471	491	235	113	1,310

(N). 1875.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	206	127	35	9	377
Lower Managers (L)	188	258	82	34	562
Skilled Workers (S)	30	50	77	22	179
Unskilled Workers (U)	13	23	22	21	79
Row sum	437	458	216	86	1,197

(O). 1879.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	192	108	27	7	334
Lower Managers (L)	168	227	69	31	495
Skilled Workers (S)	27	43	77	18	165
Unskilled Workers (U)	12	18	19	16	65
Row sum	399	396	192	72	1,059

Note: These are the transition matrices of the C1820 sample by observation year of the father. Sons' occupations are categorized around the age of forty.

2C Census Sample

In this section, we conduct an analysis of social mobility in the second sub-sample mentioned in Section 2.2. We combine the registered residents' data with data on citizens that lived in the city of Zurich (henceforth called census sample). Consequently, we exclude all geographically mobile individuals. This extension addresses a separate research question. It quantifies the level of mobility in the city of Zurich for a changing population rather than the level of mobility in a homogeneous population irrespective of its location. The presented results might be better comparable with existing (international) studies on intergenerational mobility due to a similar sample selection (excluding emigrants and including residents). Note that we are not able to replicate the entire resident population of Zurich as we lack information on temporary foreign residents. Moreover, the collection of the registered residents' data is still ongoing. Thus, we only have the full count of residents and citizens available in the historical sources for the years 1819, 1830, 1840, and 1889. The census sample in the remainder of the analyzed years consists predominantly of citizens residing in the city. We still show the full set of observation years to get a first continuous estimate of intergenerational occupational mobility in the city of Zurich for the entire nineteenth century.[23]

Descriptive Statistics Figure 2C.1 entails the occupational distribution employing both the SEP and the Long-Ferrie categorizations. We see a similar structural change as in the C1820 sample in the main part of this paper. The relative share of middle SEP occupations and (lower) white-collar occupations increases over time. Overall the distribution across categories is shifted towards lower SEP and more manual work as compared to the C1820 sample. We can compare our distribution in panel (B) of Figure 2C.1 to the numbers from Norway and the United States displayed in Modalsli (2017, Figure 1). We find that (excluding the negligible share of farmers) Zurich's population exhibited a higher fraction of white-collar occupations and fewer unskilled manual occupations. This seems reasonable considering that Zurich as a city is compared to the entire country of Norway and the United States consisting of both rural and urban areas. Interestingly, we still observe the same trend towards white-collar occupations in all locations. This is most likely due to the common industrialization process in the second half of the nineteenth century.

Absolute Mobility A first glance at absolute social mobility is provided in Figures 2C.2, 2C.3, and 2C.4 displaying the transition probabilities based on the transition matrices presented in in Tables 2C.3, 2C.4, and 2C.5. Again, we find a very similar picture to our main analysis. We observe high occupational persistence (a strong diagonal) and

[23] More precisely, we present results for all intersecting years of residents' and citizens' information. In the intergenerational analyses, we focus again on 1819–1879.

increasing probabilities to enter middle SEP and (lower) white-collar occupations. For a similar period (1860–1910), Modalsli (2017, Figure 2) infers weakly increasing transition probabilities between categories. This result is not mirrored in Zurich. However, the transition probabilities remain relatively flat over time as in the analysis on Norway.

Relative Mobility Figure 2C.5 provides the two-way log-odds ratios accounting for structural changes in the occupational distribution. We find that the ratios are overall flatter but higher (less mobile) than the ratios of our citizens' sample. If anything, relative mobility seems to have been weakly decreasing. The odds increased for middle and high SEP, (higher) white-collar, skilled, and unskilled manual occupations whereas they decreased for low SEP and lower white-collar occupations. Interestingly, we observe that the log-odds ratio of unskilled workers exhibited a kink increasing strongly until 1872 and decreasing thereafter. This kink hints towards a change in the trend of mobility for the group of unskilled workers by the end of the nineteenth century. Modalsli (2017, Figure 3) depicts that, in Norway, white-collar occupations exhibited a pronounced increase in mobility in a similar period. If anything, we observe the opposite of weakly decreasing mobility. Overall, the level of immobility as measured by two-way log-odds ratios was weakly lower in Zurich than in Norway.

The conventional Altham statistics in the first column of Table 2C.1 suggest that mobility decreased in the first part of the period. For the second half of the period, the SEP and the baseline Long-Ferrie classification exhibit some fluctuations and a small increase in intergenerational mobility. The extended Long-Ferrie categorization displays fluctuations as well but indicates a weakly decreasing level of social mobility for the same period. Interestingly, the transition matrices seem to be structurally similar over the course of the entire period as none of the comparisons with 1819 (displayed in the second column (AS1819) of Table 2C.1) are statistically significant on the 1 percent level. Figure 2C.6 shows that controlling for a quadratic function of age for both fathers and sons does not change the results' patterns. Both M and M' displayed in Table 2C.1 (third and sixth column) paint a picture of decreasing mobility over the entire period across all categorizations. The drop in absolute mobility appears to be driven by a reduction in both downward and upward mobility as outlined in panel (A).[24] Overall, upward mobility was more prevalent than downward mobility.

Correlation Coefficient The evolution of our measure of intergenerational correlation employing standardized HISCAM scores is displayed in Figure 2C.7. We find no clear pattern over time but only insignificant fluctuations between approximately 0.35 and 0.40. The level of the estimates is comparable to the ones in our main analysis and thus

[24] Remember: only when employing the SEP categorization, one can interpret a change towards "higher occupations" (in this case higher SEP) as upward mobility.

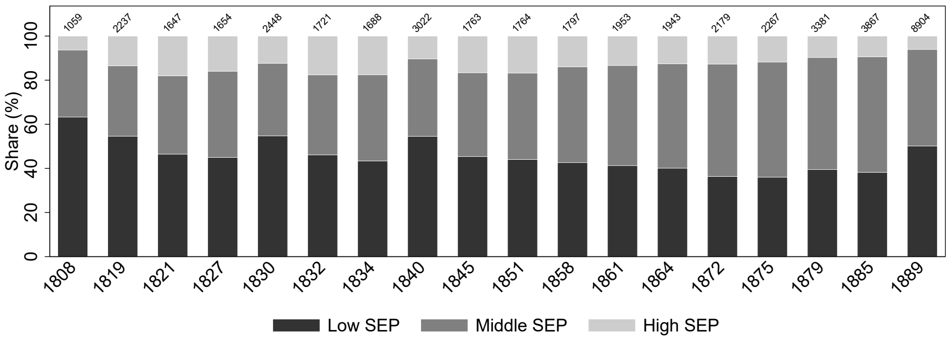
to existing estimates of earnings and education correlation coefficients. We are not able to observe the pattern of weakly decreasing mobility in our census sample that most other measures suggest.

Farmers Table 2C.2 presents the conventional Altham statistics when including farmers into all categorizations and compares the results to the baseline without farmers. On the one hand, we find qualitatively very similar results when including and excluding farmers employing the SEP classification. On the other hand, the inclusion of farmers in the Long-Ferrie classifications implies a much stronger decrease in occupational mobility in the second half of the period and an overall higher level of immobility. Firstly, the higher levels might be partially driven by the small relative share of both unskilled manual and farming occupations in the sample. Because of the small sizes, transitions between the two categories are unlikely over the entire course of the century. Hence, we are not able to estimate the Altham statistic over the entire period (only possible for 1834–1851 and 1864–1879). Secondly, the contrasting results regarding the level indicate that the transition between farming occupations and other occupations was not evenly distributed, especially in the manual sector. Apparently, transitions between farming occupations and unskilled occupation were less likely and becoming even less likelier over time than transitions between farming occupations and low SEP occupations. Thus, our results differ to some extent for the different classifications, while they still agree on weakly declining occupational mobility.

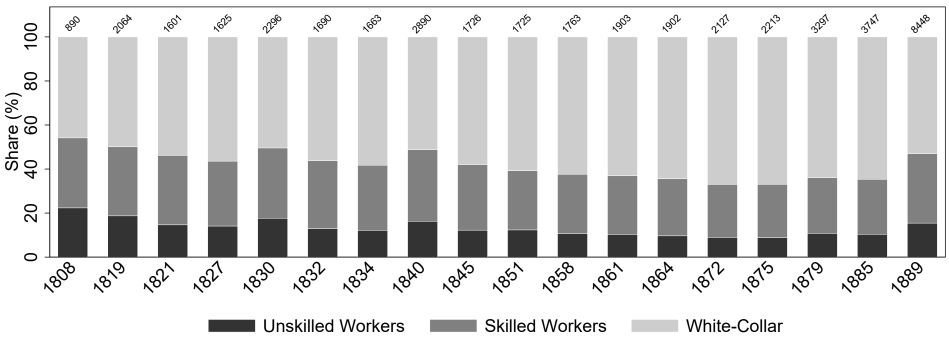
We can compare the fourth and the last column of Table 2C.2 with the estimates provided by Long and Ferrie (2013), Modalsli (2017), and Pérez (2019). Our estimates for 1834 are roughly comparable to the estimates Long and Ferrie (2013) provide for the United States between 1850 and 1900. After the decrease in mobility (e.g. in 1879), our estimates are better comparable to the ones of Long and Ferrie (2013) for the United Kingdom between 1851 and 1881 and the ones of Modalsli (2017) for Norway between 1865 and 1900. Pérez (2019) finds a much higher level of mobility for Argentina between 1869 and 1895. We can conclude, that the city of Zurich experienced a decline in occupational mobility that was comparable to the difference in the level of mobility between the United States and the United Kingdom or Norway around the same time. Of course, one has to account for the fact that Zurich was only a city and thus a lot smaller regarding the number of individuals and also more homogeneous with respect to the occupational sectors. Thus, this comparison is merely illustrative and does not allow for too thorough interpretations.

Figure 2C.1. Occupational structure over time in the census sample.

(a). SEP categories.



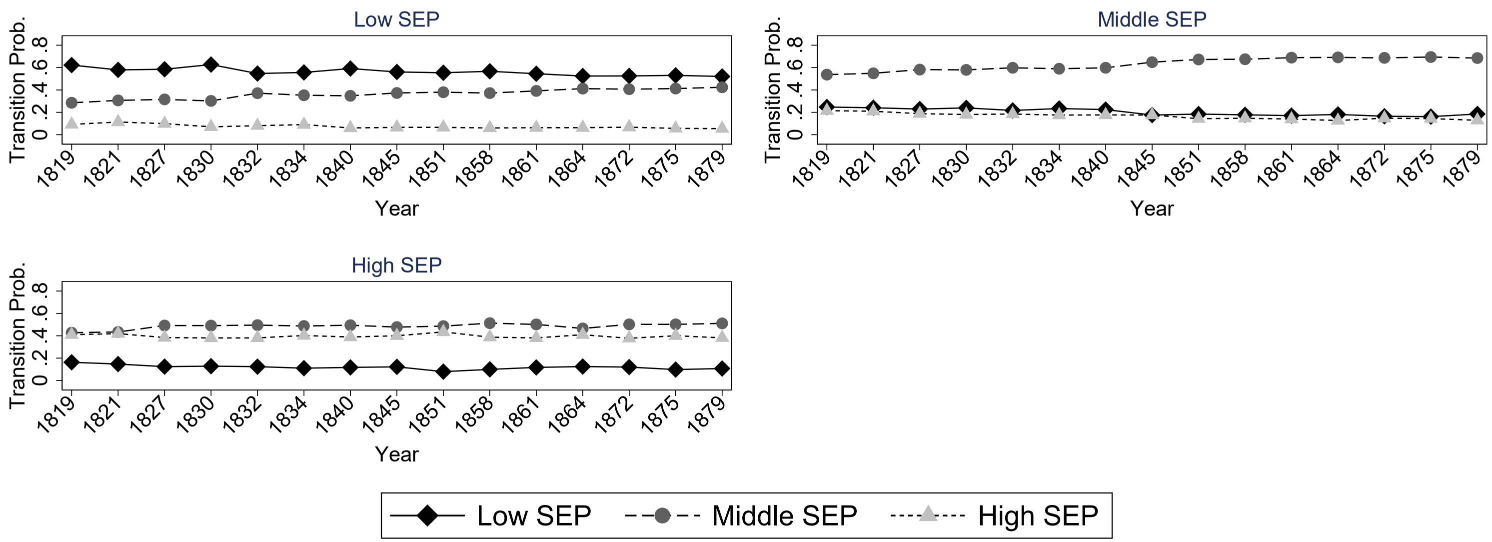
(b). Baseline Long-Ferrie categorization.



(c). Extended Long-Ferrie categorization.

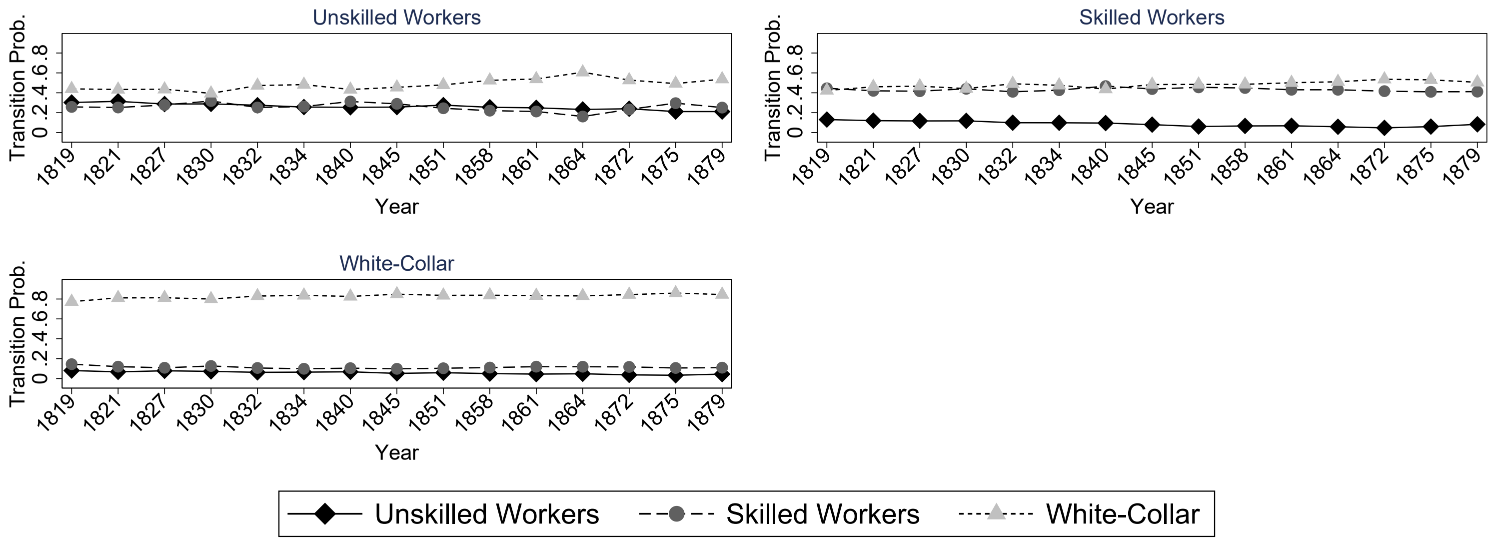
Note: These figures include every citizen residing in the city of Zurich and all registered residents in the data. The numbers above the columns denote the number of observations per year.

Figure 2C.2. Transition probabilities over time with SEP categorization—census sample.



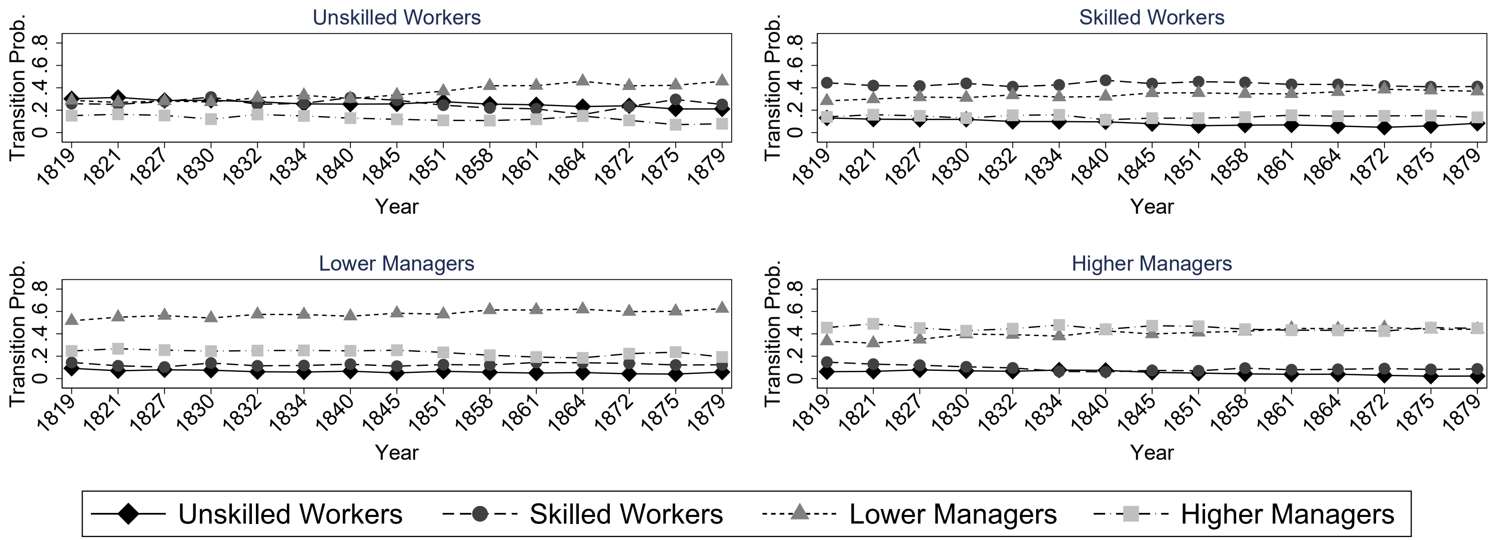
Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father. For example, the upper-left panel displays the transition probabilities of sons whose fathers had a low SEP occupation in the corresponding year.

Figure 2C.3. Transition probabilities over time with baseline Long-Ferrie categorization—census sample.



Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father.

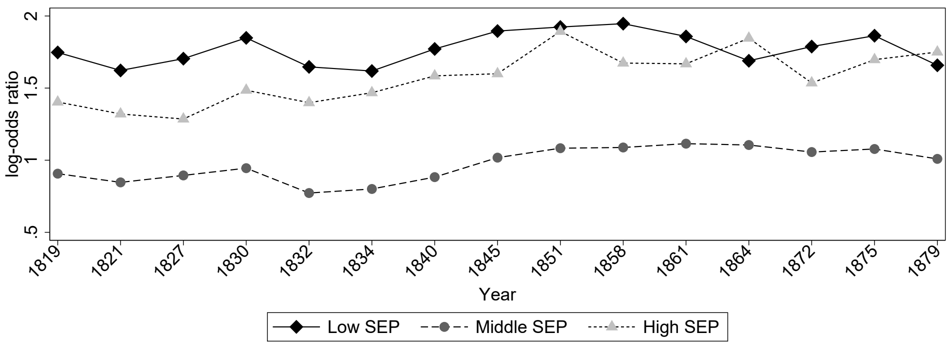
Figure 2C.4. Transition probabilities over time with extended Long-Ferrie categorization—census sample.



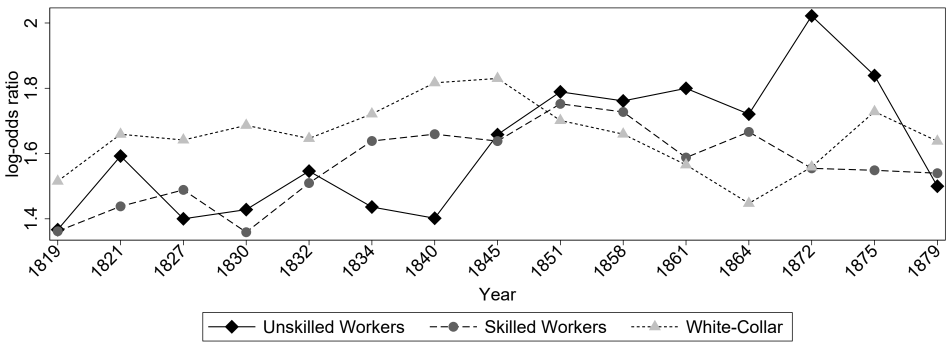
Note: These are the probabilities of sons' occupations around the age of forty (lines) conditional on the fathers' occupations (panel titles). Year denotes the observation year of the father.

Figure 2C.5. Log-odds ratios over time—census sample.

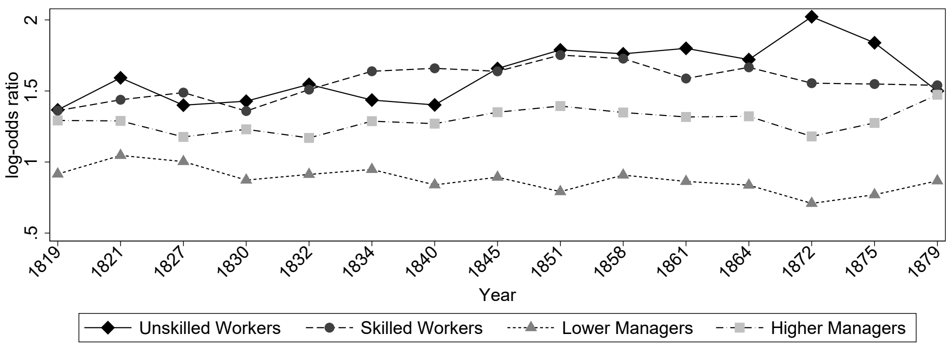
(a). SEP categories.



(b). Baseline Long-Ferrie categorization.



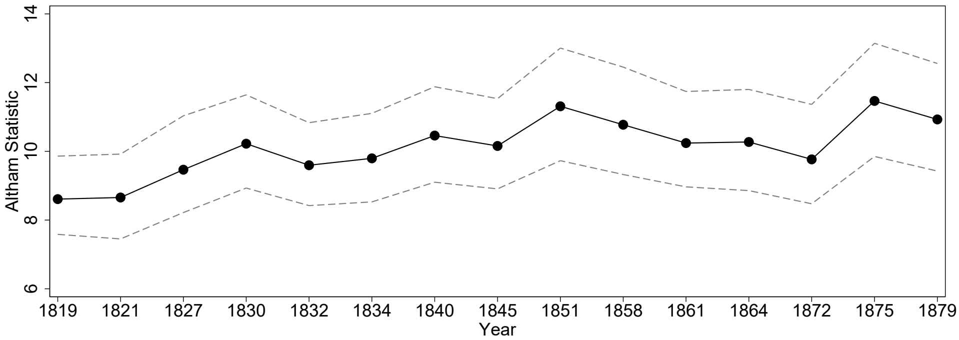
(c). Extended Long-Ferrie categorization.



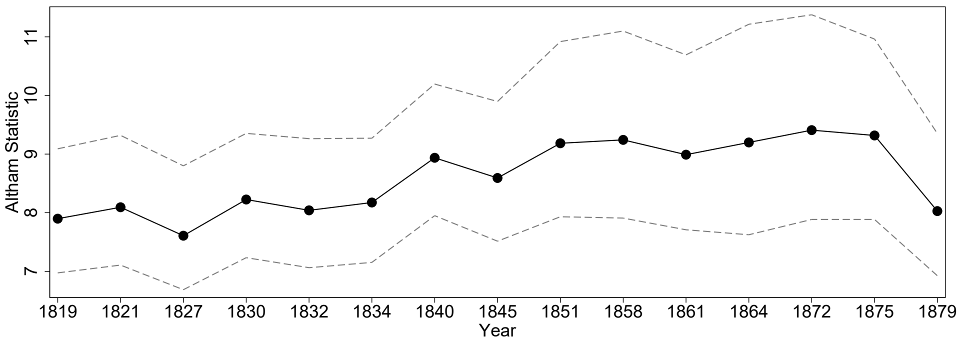
Note: These are the log-odds ratios $\Theta_{2,i}$, with $i \in \{1, 2, 3, (4)\}$ representing the three SEPs (low, middle, and high) or three/four Long-Ferrie categories (white-collar (higher and lower), skilled workers, and unskilled workers). One can read panel (a). as follows: e.g. the son of a father with a low SEP occupation in 1819 was approximately $e^{1.75} = 5.75$ times more likely to enter a low SEP occupation compared to middle or high SEP occupations than the son of a father with a middle or high SEP occupation.

Figure 2C.6. Altham statistic controlled for age and age squared of both the son and father over time—census sample.

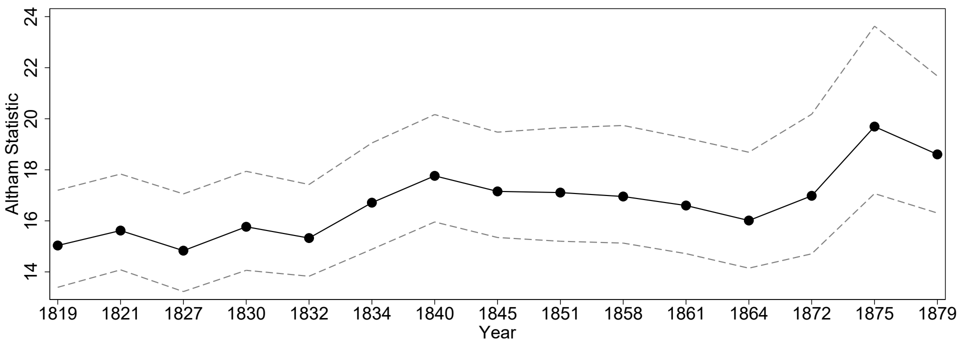
(a). SEP categories.



(b). Baseline Long-Ferrie categorization.

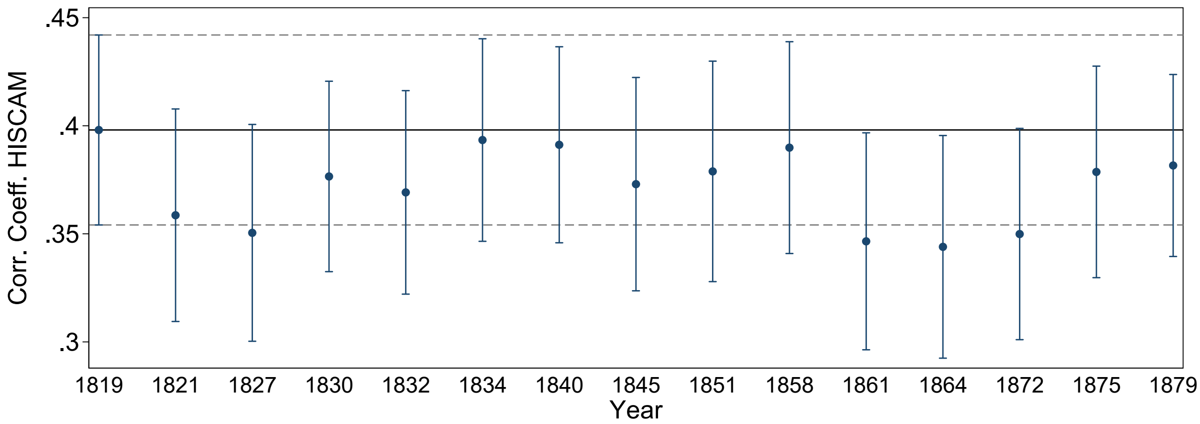


(c). Extended Long-Ferrie categorization.



Note: These are the Altham statistics controlled for a quadratic function of father's and son's age following Modalsli (2015). The confidence intervals are calculated by the same bootstrap technique as presented in Modalsli (2015, p. 8).

Figure 2C.7. Correlation coefficient of the standardized HISCAM measure over time—census sample.



Note: The solid (dashed) black line represents our estimate (confidence intervals) for the year 1819. How we arrive at this correlation coefficient is explained in Section 2.3.

Table 2C.1. Measures of mobility over time—census sample.

(a). SEP categories.

Year	AS	AS1819	M	U	D	M'	U'	D'
1819	8.90***	0.00	44.07	26.13	17.94	44.07	26.13	17.94
1821	8.42***	0.88	45.99	26.26	19.73	44.83	26.24	18.59
1827	9.14***	1.13	44.52	24.99	19.53	43.99	25.66	18.33
1830	10.16***	1.44	42.82	24.04	18.78	42.91	25.44	17.47
1832	9.32***	0.88	46.08	26.50	19.58	44.67	26.45	18.21
1834	9.59***	1.61	45.49	25.43	20.06	44.45	25.97	18.48
1840	10.64***	2.05	43.30	25.87	17.43	43.10	25.81	17.30
1845	10.41***	1.76	42.77	26.44	16.33	41.57	25.26	16.32
1851	11.78***	3.32*	41.75	24.72	17.02	40.20	24.11	16.09
1858	11.14***	2.37	41.23	23.81	17.42	40.49	24.42	16.06
1861	10.44***	1.84	41.33	24.59	16.74	40.84	24.68	16.16
1864	10.37***	2.42	40.99	24.34	16.65	41.20	24.88	16.32
1872	10.04***	1.53	40.90	24.26	16.65	41.57	25.09	16.48
1875	11.28***	2.66	39.95	23.98	15.97	40.44	24.56	15.89
1879	10.82***	2.49	41.02	25.02	15.99	41.84	25.20	16.64

(B). Baseline Long-Ferrie categorization.

Year	AS	AS1819	M	U	D	M'	U'	D'
1819	7.16***	0.00	40.18	24.02	16.16	40.18	24.02	16.16
1821	7.91***	0.94	37.14	22.98	14.16	38.79	23.55	15.24
1827	7.58***	1.47	36.10	21.65	14.45	39.27	24.02	15.25
1830	7.70***	1.53	38.30	23.74	14.56	39.34	24.05	15.29
1832	7.85***	1.11	36.12	23.36	12.76	38.75	23.65	15.10
1834	7.89***	1.49	35.03	22.47	12.55	38.27	23.46	14.81
1840	8.18***	2.12	35.09	22.21	12.88	37.85	23.45	14.40
1845	8.60***	2.06	34.21	23.02	11.19	37.22	23.11	14.11
1851	9.07***	2.95	32.99	21.25	11.74	37.02	23.06	13.95
1858	8.63***	2.12	32.27	20.24	12.04	37.49	22.92	14.56
1861	8.42***	1.91	33.12	20.81	12.31	38.30	23.11	15.20
1864	8.63***	3.07	32.20	19.59	12.60	38.76	23.22	15.54
1872	9.05***	2.87	31.12	19.54	11.57	38.05	23.32	14.73
1875	8.55***	1.90	30.84	20.00	10.84	38.13	23.45	14.68
1879	7.59***	0.49	33.84	21.91	11.92	39.12	23.58	15.55

(C). Extended Long-Ferrie categorization.

Year	AS	AS1819	M	U	D	M'	U'	D'
1819	14.41***	0.00	55.04	32.38	22.65	55.04	32.38	22.65
1821	15.24***	2.29	53.46	32.44	21.02	53.41	31.97	21.44
1827	14.72***	3.26	53.44	31.80	21.65	54.27	32.69	21.58
1830	15.70***	4.02	54.97	32.46	22.51	55.30	32.92	22.38
1832	15.02***	3.56	54.10	32.20	21.90	54.18	32.27	21.91
1834	16.28***	6.41	52.66	32.21	20.45	53.44	31.84	21.60
1840	17.60***	7.60*	53.10	31.75	21.35	54.01	32.44	21.57
1845	17.63***	6.01	52.08	32.92	19.16	52.82	32.10	20.72
1851	17.95***	6.50	51.66	30.28	21.37	52.33	31.61	20.73
1858	16.86***	4.47	50.97	28.32	22.65	52.11	31.04	21.07
1861	16.67***	5.21	51.54	28.56	22.98	52.93	30.73	22.20
1864	15.84***	5.47	50.84	27.36	23.48	52.76	30.51	22.25
1872	17.38***	5.64	52.34	28.54	23.80	53.50	31.76	21.74
1875	19.58***	7.55	51.63	29.82	21.81	53.64	32.14	21.50
1879	18.51***	6.12	51.60	29.59	22.01	53.47	31.46	22.01

Note: The mobility measures are: (AS) conventional Altham statistic $d(P, J)$ showing distance from perfect mobility, (AS1819) Altham statistic comparing each year's transition matrix with the one from 1819 to show structural mobility changes, (M) share of off-diagonal/share of mobile, (U) share of upward mobile, (D) share of downward mobile, (M') share of off-diagonal with marginal distribution adjusted to the transition matrix of 1819, (U') share of upward mobile with marginal distribution adjusted to 1819, and (D') share of downward mobile with marginal distribution adjusted to 1819. The stars indicate significance levels from the G^2-test (*: 5 %, **: 1 %, ***: 0.1 %). Degrees of freedom: 4 (A). and (B)., and 5 (C)., respectively.

Table 2C.2. Measures of mobility over time with(out) farmers—census sample.

Year	AS(S)	AS(SF)	AS(L)	AS(LF)	AS(L+)	AS(L+F)
1819	8.90***	14.65***	7.16***		14.41***	
1821	8.42***	12.85***	7.91***		15.24***	
1827	9.14***	12.85***	7.58***		14.72***	
1830	10.16***	14.10***	7.70***		15.70***	
1832	9.32***	13.15***	7.85***		15.02***	
1834	9.59***	13.08***	7.89***	15.02***	16.28***	26.03***
1840	10.64***	14.38***	8.18***	17.39***	17.60***	29.27***
1845	10.41***	14.78***	8.60***	17.87***	17.63***	30.00***
1851	11.78***	16.67***	9.07***	19.14***	17.95***	29.45***
1858	11.14***	16.10***	8.63***		16.86***	
1861	10.44***	15.60***	8.42***		16.67***	
1864	10.37***	17.58***	8.63***	25.59***	15.84***	37.56***
1872	10.04***	16.09***	9.05***	23.96***	17.38***	34.26***
1875	11.28***	18.39***	8.55***	26.02***	19.58***	38.94***
1879	10.82***	16.66***	7.59***	25.79***	18.51***	39.63***

Note: The mobility measures are: (AS(S)) conventional Altham statistic $d(P, J)$ with SEP categorization excluding farmers, (AS(SF)) conventional Altham statistic $d(P, J)$ with SEP categorization including farmers, (AS(L)) conventional Altham statistic $d(P, J)$ with baseline Long-Ferrie categorization excluding farmers, (AS(LF)) conventional Altham statistic $d(P, J)$ with baseline Long-Ferrie categorization including farmers, (AS(L+)) conventional Altham statistic $d(P, J)$ with extended Long-Ferrie categorization excluding farmers, and (AS(L+F)) conventional Altham statistic $d(P, J)$ with extended Long-Ferrie categorization including farmers. The empty entries suggest that there were empty entries in the transition matrices preventing the estimation of the Altham statistic. In 1819 for example, none of the sons of a farmer entered an unskilled manual occupation. The stars indicate significance levels from the G^2-test (*: 5 %, **: 1 %, ***: 0.1 %). Degrees of freedom: 4 (S) and (L), 5 (SF), (LF), and (L+), and 6 (L+F), respectively.

Transition Matrices We present the transition matrices of our census sample according to all categorizations below.

TABLE 2C.3. TRANSITION MATRICES OF SEP—CENSUS SAMPLE.

(A). 1819.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	556	170	45	771
middle SEP (M)	255	369	118	742
high SEP (H)	82	148	113	343
Row sum	893	687	276	1,856

(B). 1821.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	393	162	40	595
middle SEP (M)	208	369	118	695
high SEP (H)	77	141	114	332
Row sum	678	672	272	1,622

(C). 1827.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	384	177	30	591
middle SEP (M)	207	449	119	775
high SEP (H)	65	145	93	303
Row sum	656	771	242	1,669

(D). 1830.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	537	183	36	756
middle SEP (M)	259	443	138	840
high SEP (H)	60	138	107	305
Row sum	856	764	281	1,901

(E). 1832.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	405	155	38	598
middle SEP (M)	275	428	152	855
high SEP (H)	60	132	117	309
Row sum	740	715	307	1,762

(F). 1834.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	377	168	31	576
middle SEP (M)	239	423	137	799
high SEP (H)	61	126	113	300
Row sum	677	717	281	1,675

(G). 1840.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	529	179	31	739
middle SEP (M)	311	477	131	919
high SEP (H)	54	141	103	298
Row sum	894	797	265	1,956

(H). 1845.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	436	127	33	596
middle SEP (M)	290	469	129	888
high SEP (H)	51	127	108	286
Row sum	777	723	270	1,770

(I). 1851.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	405	130	23	558
middle SEP (M)	278	475	141	894
high SEP (H)	48	101	126	275
Row sum	731	706	290	1,727

(J). 1858.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	396	139	27	562
middle SEP (M)	260	528	139	927
high SEP (H)	42	115	105	262
Row sum	698	782	271	1,751

(K). 1861.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	398	141	31	570
middle SEP (M)	286	570	133	989
high SEP (H)	46	116	101	263
Row sum	730	827	265	1,822

(L). 1864.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	350	153	29	532
middle SEP (M)	275	583	108	966
high SEP (H)	42	107	95	244
Row sum	667	843	232	1,742

(M). 1872.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	320	151	27	498
middle SEP (M)	248	628	113	989
high SEP (H)	41	135	85	261
Row sum	609	914	225	1,748

(N). 1875.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	320	146	21	487
middle SEP (M)	249	628	108	985
high SEP (H)	34	130	86	250
Row sum	603	904	215	1,722

(O). 1879.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	438	205	25	668
middle SEP (M)	357	760	119	1,236
high SEP (H)	46	143	89	278
Row sum	841	1,108	233	2,182

Note: These are the transition matrices of the census sample by observation year of the father. Sons' occupations are categorized around the age of forty.

Table 2C.4. Transition matrices of the baseline Long-Ferrie categorization—census sample.

(a). 1819.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	724	233	119	1,076
Skilled Workers (S)	136	245	70	451
Unskilled Workers (U)	76	72	82	230
Row sum	936	550	271	1,757

(b). 1821.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	730	207	98	1,035
Skilled Workers (S)	108	189	57	354
Unskilled Workers (U)	61	54	71	186
Row sum	899	450	226	1,575

(c). 1827.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	798	203	91	1,092
Skilled Workers (S)	107	181	58	346
Unskilled Workers (U)	77	51	60	188
Row sum	982	435	209	1,626

(d). 1830.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	800	232	108	1,140
Skilled Workers (S)	127	231	87	445
Unskilled Workers (U)	73	62	79	214
Row sum	1,000	525	274	1,799

(e). 1832.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	831	238	105	1,174
Skilled Workers (S)	107	199	56	362
Unskilled Workers (U)	63	48	61	172
Row sum	1,001	485	222	1,708

(F). 1834.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	812	222	94	1,128
Skilled Workers (S)	96	199	51	346
Unskilled Workers (U)	63	46	50	159
Row sum	971	467	195	1,633

(G). 1840.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	894	233	104	1,231
Skilled Workers (S)	114	249	75	438
Unskilled Workers (U)	74	51	61	186
Row sum	1,082	533	240	1,855

(H). 1845.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	855	236	96	1,187
Skilled Workers (S)	99	214	61	374
Unskilled Workers (U)	53	39	54	146
Row sum	1,007	489	211	1,707

(I). 1851.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	859	214	92	1,165
Skilled Workers (S)	107	201	47	355
Unskilled Workers (U)	61	27	53	141
Row sum	1,027	442	192	1,661

(J). 1858.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	908	211	93	1,212
Skilled Workers (S)	120	195	39	354
Unskilled Workers (U)	55	29	45	129
Row sum	1,083	435	177	1,695

(K). 1861.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	936	220	104	1,260
Skilled Workers (S)	135	189	41	365
Unskilled Workers (U)	51	30	48	129
Row sum	1,122	439	193	1,754

(L). 1864.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	923	209	94	1,226
Skilled Workers (S)	133	176	25	334
Unskilled Workers (U)	54	24	36	114
Row sum	1,110	409	155	1,674

(M). 1872.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	947	215	77	1,239
Skilled Workers (S)	132	167	34	333
Unskilled Workers (U)	42	19	35	96
Row sum	1,121	401	146	1,668

(N). 1875.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	948	220	70	1,238
Skilled Workers (S)	118	170	42	330
Unskilled Workers (U)	37	25	30	92
Row sum	1,103	415	142	1,660

(O). 1879.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,123	286	122	1,531
Skilled Workers (S)	146	233	57	436
Unskilled Workers (U)	60	47	48	155
Row sum	1,329	566	227	2,122

Note: These are the transition matrices of the census sample by observation year of the father. Sons' occupations are categorized around the age of forty.

Table 2C.5. Transition matrices of the extended Long-Ferrie categorization—census sample.

(a). 1819.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	155	147	77	41	420
Lower Managers (L)	114	308	156	78	656
Skilled Workers (S)	50	86	245	70	451
Unskilled Workers (U)	21	55	72	82	230
Row sum	340	596	550	271	1,757

(b). 1821.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	167	149	72	37	425
Lower Managers (L)	108	306	135	61	610
Skilled Workers (S)	44	64	189	57	354
Unskilled Workers (U)	22	39	54	71	186
Row sum	341	558	450	226	1,575

(c). 1827.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	151	165	65	32	413
Lower Managers (L)	117	365	138	59	679
Skilled Workers (S)	40	67	181	58	346
Unskilled Workers (U)	26	51	51	60	188
Row sum	334	648	435	209	1,626

(d). 1830.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	154	157	68	33	412
Lower Managers (L)	143	346	164	75	728
Skilled Workers (S)	38	89	231	87	445
Unskilled Workers (U)	25	48	62	79	214
Row sum	360	640	525	274	1,799

(e). 1832.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	177	151	75	36	439
Lower Managers (L)	156	347	163	69	735
Skilled Workers (S)	38	69	199	56	362
Unskilled Workers (U)	26	37	48	61	172
Row sum	397	604	485	222	1,708

(F). 1834.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	163	159	74	29	425
Lower Managers (L)	129	361	148	65	703
Skilled Workers (S)	22	74	199	51	346
Unskilled Workers (U)	26	37	46	50	159
Row sum	340	631	467	195	1,633

(G). 1840.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	162	177	61	31	431
Lower Managers (L)	157	398	172	73	800
Skilled Workers (S)	22	92	249	75	438
Unskilled Workers (U)	27	47	51	61	186
Row sum	368	714	533	240	1,855

(H). 1845.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	161	169	63	25	418
Lower Managers (L)	136	389	173	71	769
Skilled Workers (S)	25	74	214	61	374
Unskilled Workers (U)	19	34	39	54	146
Row sum	341	666	489	211	1,707

(I). 1851.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	181	150	57	21	409
Lower Managers (L)	160	368	157	71	756
Skilled Workers (S)	27	80	201	47	355
Unskilled Workers (U)	19	42	27	53	141
Row sum	387	640	442	192	1,661

(J). 1858.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	188	137	60	19	404
Lower Managers (L)	180	403	151	74	808
Skilled Workers (S)	40	80	195	39	354
Unskilled Workers (U)	18	37	29	45	129
Row sum	426	657	435	177	1,695

(k). 1861.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	180	136	68	23	407
Lower Managers (L)	187	433	152	81	853
Skilled Workers (S)	33	102	189	41	365
Unskilled Workers (U)	16	35	30	48	129
Row sum	416	706	439	193	1,754

(l). 1864.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	176	130	60	23	389
Lower Managers (L)	182	435	149	71	837
Skilled Workers (S)	34	99	176	25	334
Unskilled Workers (U)	16	38	24	36	114
Row sum	408	702	409	155	1,674

(m). 1872.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	190	150	60	16	416
Lower Managers (L)	204	403	155	61	823
Skilled Workers (S)	40	92	167	34	333
Unskilled Workers (U)	13	29	19	35	96
Row sum	447	674	401	146	1,668

(n). 1875.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	188	163	63	10	424
Lower Managers (L)	182	415	157	60	814
Skilled Workers (S)	34	84	170	42	330
Unskilled Workers (U)	9	28	25	30	92
Row sum	413	690	415	142	1,660

(o). 1879.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	218	163	77	18	476
Lower Managers (L)	214	528	209	104	1,055
Skilled Workers (S)	42	104	233	57	436
Unskilled Workers (U)	11	49	47	48	155
Row sum	485	844	566	227	2,122

Note: These are the transition matrices of the census sample by observation year of the father. Sons' occupations are categorized around the age of forty.

Chapter 3

Bias in Social Mobility Estimates with Historical Data Evidence from Swiss Microdata

Abstract: This paper explores a variety of potential issues one has to address when estimating intergenerational mobility with historical data. Many studies are potentially affected by bias originating from individuals emigrating and thus dropping out of the sample, missing information on the life-cycle, and imperfectly linking data sets. Unique panel data on Zurich's citizenry between 1799 and 1926 entail information on true intergenerational links, and allow to follow individuals across the globe and time. This enables me to explore how father-son mobility estimates are affected by excluding emigrating individuals, occupational patterns over the life-cycle, and linking procedures. The results suggest that focusing on geographically immobile individuals might decrease the estimated level of social mobility. The estimated level of mobility depends on both the father's and the son's age at classification without a monotone trend in the direction of the bias. Most recent linking procedures do not generate significant bias in the sample of Zurich citizens due to the high level of detail of the data combined with a small population size.

JEL classification: J62, J61, N33, N34.
Keywords: Social Mobility, Geographic Mobility, Life-cycle, Matching, Historical Data.

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3.1 Introduction

Does everyone have an equal chance of being economically successful? Or is socioeconomic status transmitted from one generation to the other such that the under-privileged are forever excluded from money and power? These questions are generally discussed in the literature on intergenerational mobility. Unique panel data of Zurich's citizenry between 1799 and 1926 allow me to contribute to the existing literature in another dimension by addressing the question: how large are the deviations in social mobility estimates originating from geographic mobility, life-cycle patterns, and data linkage?

Usually, studies on social mobility depend on linking census data or birth registers to retrieve intergenerational links and thus obtain information on two or more generations (e.g. Ferrie, 2005; Bourdieu et al., 2009; Long, 2013; Long and Ferrie, 2013; Dribe et al., 2015; Barone and Mocetti, 2016; Collins and Wanamaker, 2017; Modalsli, 2017; Feigenbaum, 2018; Pérez, 2019). A similar procedure is necessary to follow individuals over the course of their life or to track emigrants to their host country[1] (e.g. Abramitzky et al., 2012; Abramitzky and Boustan, 2017). Thus, most studies omit emigrants and are not able to address potential life patterns in occupations.

The data at hand allow to estimate intergenerational mobility taking all of these potential sources of bias into consideration (as in Chapter 2). Even more importantly, it is possible to quantify the magnitude and direction of the mentioned distortions as the employed data set includes true intergenerational links, allows me to track individuals over the course of their lives, and even provides information after emigration. I employ different measures of intergenerational mobility to control for the variety of measures in the existing literature. Hence, the main research questions in this paper are: (1) How are social mobility estimates affected by the in- and exclusion of migrants, life-cycle patterns in occupational outcomes, and the linking procedure, and (2) what is the relative size of the resulting deviations across different measures of mobility? By answering these questions, this paper also contributes to the literature on geographic mobility, life-cycle bias, and linking procedures.

The bulk of the literature on the economics of (international) migration tackles the assimilation of immigrants in their host countries (Hatton and Williamson, 1994b; Constant and Zimmermann, 2013), which is directly linked to the intergenerational persistence of

[1] Throughout this article, host and destination country/continent will be used interchangeably.

socioeconomic status.[2] Fewer researchers have focused on the selection of international migrants in their country of origin, particularly in a historical context. Notable exceptions are Wegge (1999, 2002, 2010), who finds that emigrants in mid-nineteenth century Germany were intermediately selected with respect to their socioeconomic positions, and Abramitzky et al. (2012, 2013), who provide evidence on negative selection among migrants from Norway to the United States during the second half of the nineteenth century.[3] This paper's contribution to the scarce literature on selection of international migrants in a historical context is twofold. First, I will provide suggestive evidence on the selection of international migrants in nineteenth century Switzerland and the effect on estimates of social mobility. Second, I investigate whether the selection of migrants differed across host countries grouped by continent.

What are potential issues when employing non-longitudinal data sets? Income, wealth, occupation, and to some extent even education change over an individual's course of life. Hence, a person's socioeconomic status at one specific point in time might not be representative of the "lifetime" socioeconomic status. This results in life-cycle bias.[4] In this paper, I will investigate whether individuals also exhibit a life pattern with respect to occupational categories in a historical context. Further, I will explore whether implied father-son mobility differs across different ages at classification of both the father's and the son's generation.

Record linkage is widely applied in both historical and contemporaneous research contexts (Ruggles et al., 2018 provide an overview). Consequently, many researchers aim at automating and improving linking procedures[5] or evaluating existing mechanisms (Eriksson, 2017; Massey, 2017; Bailey et al., 2019). The latter strand of literature compares different record linking procedures with "ground truth" data featuring the highest achievable matching rates. Both Bailey et al. (2019) and Eriksson (2017) investigate the effect

[2]See e.g. Borjas (1992, 1993, 1994, 1995), Hammarstedt and Palme (2006), and Ward (2017) on historical migration waves or Card (2005), Bauer and Riphahn (2007), Bratsberg et al. (2010, 2014), and Favre et al. (2018) on more recent migration waves.

[3]See Abramitzky and Boustan (2017) on a review of migration flows to the United States and Hatton and Williamson (1994b), Hatton and Williamson (2005), or Ferrie and Hatton (2014) for further research on the selection of international migrants in a historical context.

[4]Solon (1999) surveys some research on life-cycle bias in intergenerational mobility estimates. Life-cycle bias is found to be large and of varying direction (Jenkins, 1987; Grawe, 2006; Nybom and Stuhler, 2016a). Thus, one strand of the literature has focused on correcting for this bias (Haider and Solon, 2006; Böhlmark and Lindquist, 2006; Nybom and Stuhler, 2016b; Gregg et al., 2017).

[5]See e.g. Scheuren and Winkler (1993), Ferrie (1996, 2004), Christen and Goiser (2007), Herzog et al. (2007), Goeken et al. (2011), Baskerville et al. (2014), Abowd (2017), Bailey et al. (2017), Abramitzky et al. (2012, 2014, 2019).

of record linkage on estimates of historical social mobility. They establish their benchmark "ground truth" data employing additional information on ancestors, which is not contained in other studies' data, resulting in matched data sets with higher quality. This paper, on the other hand, is the first to evaluate linking precision of linking procedures and the related bias in intergenerational mobility estimates in a historical context based on *observable* intergenerational links.

I find that Swiss emigrants were on average intermediately selected in the nineteenth century, and that this selection differed strongly by destination continent. Individuals migrating within Europe were more positively selected than those emigrating to the United States or Canada. This selection translates into different estimates of intergenerational mobility. Emigrants were, on average, more mobile than geographically immobile individuals. Further, individuals in the data exhibited occupational life patterns suggesting that they experienced upward intragenerational mobility. The older a citizen, the more likely he was to obtain a higher socioeconomic position. These life patterns affect the point estimates of intergenerational mobility to some extent. However, these biases do not exhibit a monotone trend nor do the patterns agree across measures of occupational mobility. Finally, state-of-the-art automated linking procedures perform neatly. They are able to match around 77 to 95 percent of all father-son pairs with rates of false matches in the single-digit per mille range. This is mostly caused by the small sample size and the high quality of the data. Still, linked samples do not exhibit structurally different estimates of intergenerational mobility in this sample of Zurich citizens in the nineteenth century.

The remainder of this paper is structured as follows. Section 3.2 describes the employed data. The main results are presented in Section 3.3. Section 3.4 concludes.

3.2 Data and Descriptive Statistics

Data Source The data originate from the same twenty-five editions of the directory of citizens of the city of Zurich between 1799 and 1926 as described in Chapter 2. This source contains the universe of Zurich's adult male citizenry. Every edition of the directory of citizens includes references to individuals' direct male relatives. As citizenship is inherited for men (jus sanguinis), the son of a citizen is a citizen as well, irrespective of his place of residence. Hence, the data feature observable intergenerational links of the male lineages.

The information on individuals includes the first name, middle names, the last name, the place of family origin[6], the year of birth, the year of death, the place of residence, occupations, the number of houses owned, the military rank, and public offices (e.g. member of the municipality council) for several points in time. Information on women is scarcer. Daughters of citizens are indirectly referred to through their father with name and year of birth (unmarried) or with information on the husband (married). Wives are also indirectly referred to through their husbands by name, year of birth, and place of origin.

The key features of the data I exploit in this paper are threefold. First, the data contain information on the occupation and place of residence of citizens living abroad. As explained in Chapter 2, the information on emigrants was partially acquired through foreign authorities and partially by mail-in forms. If no current information was available, the directory contains the latest available characteristics including their date and a note that the corresponding citizen was currently untraceable.[7] Hence, the data allow to track citizens across the globe and to observe their occupation. Second, the frequent release of a new citizens' directory (every two to eleven years) and its cross-section character allow to track citizens over time. Thus, I am able to observe the life pattern of occupations for all citizens. Third, the data contain observable intergenerational links through the cross-reference to all male relatives of a citizen. Consequently, there is no need for linking fathers to sons in an automated procedure.

Classifications of Occupations I employ the same set of occupational classifications as described in Chapter 2. For the main part of the analysis, I divide occupations into low, middle, and high socioeconomic positions (SEP). This division is based on the categorization introduced by Schüren (1989) for occupations in nineteenth century Germany. The most prevalent occupations in the low SEP category are locksmith, mechanic, and baker. Merchants dominate the middle SEP category, but also engineer and teacher are frequent occupations with middle SEP. Lastly, the high SEP category's most frequent occupations are priest, physician, and professor. The upside of this categorization is that one can interpret the classes in an ordinal manner. Most of the mobility measures employed do

[6]This information conveys the origin of the family before it was naturalized in Zurich dating back to even before the thirteenth century.

[7]The data lack information on emigrant citizens in only 0.63 percent of all entries (across all observation years).

not rely on this feature but the ordinal distinction of occupations allows to shed light on e.g. the selection of migrants in greater detail. Farmers are excluded throughout the entire analysis as their share in Zurich's citizenry is negligible.

For better international comparability, I employ an alternative categorization similar to Long and Ferrie (2013), Modalsli (2017), and Pérez (2019). Occupations are first divided into manual and non-manual labor. The manual workers are subsequently split into an unskilled workers group (requires little to no training) and into a skilled workers group (requires some training or education). The non-manual workers are classified as white-collar workers. In a more detailed classification the white-collar workers can be split into lower and higher managers.[8] This classification is based on the Historical International Standard Classification of Occupations (HISCO) according to Van Leeuwen et al. (2002) that allows to map occupations into the Historical International Social Class Scheme (HISCLASS, Van Leeuwen and Maas, 2011).[9] Throughout the paper, this classification is referred to as Long-Ferrie (three groups) or extended Long-Ferrie (four groups) categorization.

Samples and Descriptive Statistics To analyze the three potential sources of bias, the data have to be split accordingly. On the one hand, one needs to generate a baseline sample that should capture the "true" level of mobility. On the other hand, one has to get a hold of each source of bias through separate sub-samples. Below, I describe each of the samples separately.

The baseline sample in this paper consists of all father-son pairs that are available in Zurich's citizenry between 1799 and 1926. In contrast to Chapter 2, I do not divide the sample across time as the focus does not lie on changes in the level of mobility over time but on the size and direction of bias. Every individual is categorized according to his occupation around the age of forty with respect to both the SEP and Long-Ferrie classifications.[10] Some descriptive statistics on the baseline sample are provided in Table 3.1. There are over 11,000 father-son pairs whereby one father may have several sons. Due to

[8] The most frequent occupations per category are: priest, physician, and engineer (higher white-collar group), merchant, shop clerk, and innkeeper (lower white-collar group), mechanic, baker, and blacksmith (skilled workers), and mercenary, upholsterer, and glazier (unskilled workers).

[9] The HISCLASS groups are distributed across occupational categories as follows: HISCLASS 1–2 (higher white-collar), HISCLASS 3–5 (lower white-collar), HISCLASS 6–7 (skilled workers), HISCLASS 9–12 (unskilled workers), and HISCLASS 8 (farmers—omitted).

[10] I exclude all individuals that are younger than sixteen or older than sixty-fivet at the time of observation closest to their fortieth birthday.

the structure of the data, fathers are on average older than sons at the observed occupation. There are some fathers in the early directories of citizens that are already older than forty. Similarly, some sons are younger than forty in the last available directories. The distribution across occupational categories is similar across the two generations.

The investigation of bias through geographic mobility requires a split of the data according to the emigration status of individuals. In this paper, I focus on international geographic mobility of sons. Thus, sons are divided into geographically immobile ("Stay"), return migrants ("Return"), and emigrants ("Emigrated"). Immobile sons may move away from the city of Zurich but remain in Switzerland. Return migrants spend some years away from Switzerland but return thereafter. Emigrants migrate to a different country and stay abroad. Both return migrants and emigrants may migrate repeatedly. To shed more light on the selection of migrants, I further split the geographically mobile group (emigrants and return migrants) by host continent (Europe, North America (NA), South America (SA), Africa (Af), Asia (As), and Australia(Au)).[11] Table 3.2 describes the three broad migrant groups and Table 3.3 contains further details on individuals by host.[12] Roughly, 70 percent of all sons never lived abroad. The remaining 30 percent leave the country, and just over 11 percent remain abroad (emigrants).

One has to categorize individuals at different ages in order to evaluate how the age at classification affects estimates of intergenerational mobility. Thus, I categorize sons according to their occupation around twenty, thirty, and forty and fathers according to their occupation around thirty, forty, and fifty.[13] Different from the baseline sample, I only allow for a deviation from the specific classification age by five years.[14] This allows to construct mobility measures for father-son pairs for every combination of son's and father's age at the observed occupation. In order not to encounter issues with comparability, I exclude every father-son pair that lacks an observation around any of the corresponding ages. Table 3.4 entails descriptive statistics of the resulting sample of 1,476 father-son pairs.

[11]As only few individuals moved to South America, Africa, Asia, and Australia, I combine the four in one group (SA/Af/As/Au). Migrants are categorized into more than one host continent if they migrate repeatedly.

[12]Table 3B.1 in Appendix 3B splits the group emigrating to South America, Africa, Asia, and Australia.

[13]I choose this set of classification ages by generation to balance the remaining sample size and age spread.

[14]So, an individual that is categorized around the age of forty has to be between thirty-five and forty-five.

Lastly, the evaluation of automated linking mechanisms requires splitting the data into fathers and sons by ignoring the observable intergenerational link and re-matching the two. First, I construct a "fathers sample" that contains all of the information on the father and only the first name, last name, and year of birth of the son. Second, I construct a "sons sample" that contains all sons as a pool of potential matches with information on the first name, middle names, last name, year of birth, and the family's place of origin. Third, I employ automated linking procedures to join the fathers with their conjectural sons. There exist many possible mechanisms to perform this kind of record linkage (for a review, see e.g. Ruggles et al., 2018). To narrow the focus down to two of the most promising linking methods, I follow the recommendations by Bailey et al. (2019) and evaluate the mechanism introduced by Ferrie (1996) and the one developed by Abramitzky et al. (2012, 2014).[15] In general, both mechanisms rely on a similar procedure. Based on first name, last name, (implied) age, and state of birth, they link individuals across time. In order to correct for orthographic differences in the spelling of names, both (may) employ phonetic corrections (NYSIIS, Soundex, or None)[16]. The basic steps of Ferrie (1996) can be condensed as follows: (1—optional) correct names phonetically, (2—optional) truncate first name after fourth letter, (3) match and discard if not born in same state, (4) allow for age differences of up to two years among matches, and (5) choose matched link with smallest difference in age. In this application, I employ the family's place of origin instead of state of birth and observe the year of birth rather than the age of individuals. The procedure of Abramitzky et al. (2012) can be wrapped up as follows: (1—optional) correct names phonetically, (2) search for exact and unique matches with respect to specified characteristics (here: first name, last name, year of birth, place of family origin), (3) if (2) was not successful, search for a match with one year of age difference, and (4) repeat (3) with a bandwidth of two years. The resulting sub-samples are described in Tables 3.5 and 3.6.

[15] Abramitzky et al. (2014) provide their code on https://ranabr.people.stanford.edu/matching-codes. A detailed description of the mechanisms can be found in Ferrie (1996) and Abramitzky et al. (2014). In this paper, I employ the same code as Bailey et al. (2019) who kindly provided me with their Stata script (Bailey and Cole, 2019).

[16] See e.g. Atack et al. (1992) for information on phonetic corrections.

3.3 Results

In this section, I present the results of the main analysis that can be split into four parts: geographic mobility (discussed in Section 3.3.1), life patterns (presented in Section 3.3.2), linking mechanisms (summarized in Section 3.3.3), and relative size of bias (analyzed in Section 3.3.4). In the first three parts, I will shed light on the three potential sources of bias in detail. The fourth part provides insights into how strongly each source of bias affects social mobility estimates compared to the others. Appendix 3A contains all transition matrices, on which the measures of mobility are based in this section.

3.3.1 Geographic Mobility

Distribution across Occupational Categories Table 3.2 reveals differences between migrants and non-migrants. The fathers of migrating individuals exhibit a shifted distribution across occupational categories towards higher SEP (white-collar) occupations as compared to fathers of non-migrating individuals. This might partially be caused by migration barriers to lower SEP individuals due to limited resources, which have been indicated in the previous literature on intercontinental migration in the early nineteenth century (Hatton and Williamson, 1994a; Baines, 1994; Faini and Venturini, 1994). The migrating sons predominantly entered middle SEP (lower white-collar) occupations, obtaining low or high SEP (skilled and unskilled worker) occupations less often than geographically immobile sons. These results are similar to the findings for nineteenth century Germany regarding the intermediate selection of emigrants (Wegge, 1999, 2002, 2010). Furthermore, sons typically migrated for the first time in their mid-twenties, which is in line with the findings of Hatton and Williamson (1994b). Interestingly, Table 3.3 suggests large differences of migrants' occupational categories by destination continent.[17] Apparently, sons with European host countries were more positively selected than those with non-European host countries. The fathers of migrants within Europe exhibited the largest share in higher SEP and white-collar occupations across all groups. Similarly, the corresponding sons were even more likely to enter high SEP occupations than the geographically immobile. This picture partially reverts for father-son pairs with sons that migrated to North America. These individuals appear to have been negatively selected

[17] Table 3B.1 in Appendix 3B contains details on individuals moving to South America, Africa, Asia, and Australia.

with respect to the SEP they entered but were still positively selected with respect to their fathers' SEPs. However, the large fraction of emigrants to North America with low SEP fathers indicates that the previously mentioned migration barriers might not have been an issue for Zurich citizens irrespective of their SEP after all. Lastly, migrants to South America, Africa, Asia, or Australia appear to have been intermediately selected with respect to SEP of both the fathers and the sons. The average age at first migration was similar across host continents with slightly higher average values for North America.[18]

Absolute Mobility I introduce a measure of absolute mobility, the fraction of mobile individuals, to start the analysis of the bias in intergenerational mobility estimates due to migration. Absolute mobility captures the experienced level of social mobility given the occupational distribution across categories. Transition matrices pose as basis for this measure of absolute mobility.[19] They contain the absolute frequency of intergenerational transitions between all possible categories. The fraction of mobile individuals can be calculated by dividing the number of sons of occupational category $i \in \{1, ..., N\}$ fathers that enter a different occupational category $\neg i$ by the total number of sons, where N denotes the number of categories.[20] If the absolute frequency of sons with category i fathers who enter occupational category j (a different category $\neg i$) is denoted by X_{ij} ($X_{i\neg i}$), the fraction of socially mobile individuals M is given by

$$M = \frac{\sum_{i=1}^{N} X_{i\neg i}}{\sum_{i=1}^{N}\sum_{j=1}^{N} X_{ij}} = \sum_{i=1}^{N} p_{i\neg i}, \tag{3.1}$$

where p_{ij} ($p_{i\neg i}$) denotes the probability that the son of an occupation i father enters category j (a different category $\neg i$).

Figures 3.1, 3.2, and 3.3 display the fraction of mobile father-son pairs by migration status and host continent. A distinction between upward (sons move towards higher SEP,

[18] A full analysis of changes in the selection of migrants over the century lies beyond the scope of this article. Especially quantifying changes in the bias by host continent becomes increasingly difficult with finer granulation of the data across time due to small sample sizes. Splitting the data mid-century reveals that overall geographic mobility increased substantially over the course of the century with a more pronounced increase of intercontinental migration. Further, migrants entered middle SEP occupations more frequently in the late than in the early nineteenth century irrespective of the host continent.

[19] Transition matrices also pose as foundation for many measures of relative mobility as presented subsequently.

[20] With both the SEP categorization and the basic Long-Ferrie categorization N is equal to three (low, middle, and high SEP and unskilled workers, skilled workers, and white-collar). In the extended Long-Ferrie categorization with a distinction between higher and lower white-collar occupations N is equal to four.

or white-collar occupations) and downward (sons move towards lower SEP, or unskilled workers occupations) mobility allows to analyze whether the sons that were socially mobile profited from this mobility or suffered from it. Note that the distinction between upward and downward mobility is more involved with the Long-Ferrie categorizations as they are not meant to be interpreted in an ordinal way. Hence, I only interpret the ratio of upward vs downward mobility employing the SEP categorization. The difference in the share of mobile individuals across migration status is small in all of the applied occupational categorizations. Shifting the focus to the continents of destination exhibits some evidence on differential rates of mobility depending on the host country. Especially with respect to the baseline Long-Ferrie categorization, there appears to be a difference between individuals that emigrated to Europe and those that emigrated to North America. Sons migrating within Europe exhibited less intergenerational mobility than those that migrated between Europe and Northern America. The split between upward and downward mobility in Figure 3.1 displays that geographically immobile sons (Stay) experienced upward mobility 1.3 times more often than downward mobility, whereas this ratio is 0.99 for emigrants. This might indicate that even if the level of absolute mobility only differed marginally between geographically mobile and immobile individuals, there were differences in the structure of social mobility. Apparently, sons migrating to European countries were also positively selected with respect to the chances of upward mobility as compared to sons that preferred North America. The former were 1.12 times more likely to experience upward mobility vs downward mobility while this ratio was 0.63 for the latter.[21]

Relative Mobility Measures of relative mobility allow to correct for the different sizes of occupational categories in the labor market.[22] Two-way log-odds ratios are one of the easiest methods to quantify relative mobility. Log-odds ratios $\Theta_{2,i}$ quantify the "advantage" sons of category i fathers had to enter the same category vs all other categories over sons of categories $\neg i$ fathers. They are defined as

$$\Theta_{2,i} = log \left[\frac{p_{ii}/(1 - p_{ii})}{p_{\neg ii}/(1 - p_{\neg ii})} \right]. \tag{3.2}$$

[21]Sons that migrated to other continents (South America, Africa, Asia, or Australia) experienced the highest chances of upward mobility as this group exhibited a ratio of 1.46.

[22]See Chapter 2 for a more detailed introduction into measures of relative mobility.

Two-way log-odds ratios by occupational category and migration status are displayed in Figures 3.4, 3.5, and 3.6. The figures provide further evidence that focusing the analysis of intergenerational mobility on stayers might lead to selection of socially less mobile individuals. For example, geographically immobile sons of high SEP fathers were 6.0 times more likely to enter high SEP occupations as well vs other occupations than sons of middle or low SEP fathers. In the baseline sample including return migrants and emigrants, this number is 4.7. Emigrating sons were only 3.5 times more likely to follow their father into a high SEP occupation vs other occupations than emigrating sons of low or middle SEP fathers. The Long-Ferrie categorizations produce qualitatively similar but quantitatively less pronounced differences. All three categorizations reveal major differences when splitting geographically mobile sons by destination. This provides further evidence on heterogeneous selection of migrants by destination continent—also with respect to the level of relative intergenerational mobility.

The two-way log-odds ratios provide evidence on differences in the level of relative intergenerational mobility by migration status when focusing on the diagonal in transition matrices, i.e. differntiating between father-son pairs with the same and those with different occupational categories. The Altham (1970b) statistic allows to retrieve a more complete analysis of the transition matrix (see also Altham and Ferrie, 2007; Long and Ferrie, 2013; Modalsli, 2015, 2017; Pérez, 2019).[23] This statistic quantifies the distance of a transition matrix P with dimension N from perfect mobility represented by a matrix of ones J. Following Modalsli (2015, 2017), one can calculate (controlled) Altham statistics by employing multinomial logistic regressions. One can regress the occupational outcome o_q^s of a son s in the father-son pair q on a set of dummies $\mathbf{D_q} = \{D_1, ..., D_N\}$ indexing the father's occupation and a set of control variables (such as age) $\mathbf{X_q}$ and estimate the Altham statistic by aggregating the coefficient estimates of the dummies. The set of $N-1$ equations (indexed by k) that have to be estimated can be denoted by

$$log\left[\frac{Pr(o_q^s = k)}{Pr(o_q^s = 1)}\right] = \alpha_k + \beta_k' \mathbf{D_q} + \gamma_k' \mathbf{X_q} + \epsilon_{k,q}, \qquad k = 2, 3, ..., N, \tag{3.3}$$

where α_k is the estimated constant, γ_k' are the coefficients of the controls, and $\beta_k' = \{\beta_k^1, ..., \beta_k^{N-1}\}$ is the parameter vector of interest. The controlled Altham statistic is then

[23] The value of the Altham statistic lies between zero and infinity (Altham, 1970b,a). This explains that the imputed confidence intervals are asymmetric in some incidences.

given by

$$d(P,J) = \left[\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}\sum_{m=1}^{N}\{(\beta_j^i - \beta_m^i) - (\beta_j^l - \beta_m^l)\}^2\right]^{1/2}. \tag{3.4}$$

Figures 3.7, 3.8, and 3.9 provide the resulting Altham statistics controlled for a quadratic function of both the son's and father's age.[24] The estimates of the Altham statistic support the insights provided by the two-way log-odds ratios: geographically immobile individuals were also socially less mobile. All occupational classifications agree with respect to the direction of the bias whereas they do not regarding the size of bias. The relatively small sample sizes when splitting geographically mobile sons by destination complicates statements about significance.[25] However, there are patterns in the point estimates. The point estimates suggest that sons migrating within Europe exhibited a lower level of mobility than e.g. migrants to North America. Overall, the estimates of relative mobility indicate that one might structurally underestimate the level of father-son mobility when excluding emigrating sons from the analysis.

Correlation Coefficient The relation between fathers' and sons' occupations can not only be classified by transition matrices but also by correlation coefficients of cardinal measures. Most studies employing intergenerational correlation coefficients focus on income, education, or elite status outcomes as a basis for the coefficients (see e.g. Black and Devereux, 2011 or Clark, 2014). The cardinal measure employed in this paper is based on occupations once again. I standardize the Historical Cambridge social interaction and stratification scales (HISCAM, Lambert et al., 2013) measure associated with each occupation's HISCO code.[26] One can regress the standardized measure of the son (s) $HISCAM_{qs}^{std}$ in the father-son pair q on the corresponding father's (f) standardized measure $HISCAM_{qf}^{std}$ according to

$$HISCAM_{qs}^{std} = \beta HISCAM_{qf}^{std} + \varepsilon_q, \tag{3.5}$$

[24] I provide the uncontrolled Altham statistics in Figures 3B.1–3B.3 in Appendix 3B.

[25] It is not possible to calculate the Altham statistic for the migrant group to South America, Africa, Asia, and Australia when employing the extended Long-Ferrie categorization because of no transitions from higher white-collar fathers to unskilled worker sons.

[26] The resulting measure has zero mean and a standard deviation of one instead of a range from 0 to 100. See also Section 2.3 in Chapter 2.

which yields the correlation coefficient β.

The correlation coefficient by migration status is depicted in Figure 3.10. The differences between the baseline sample and the sub-groups by migration status exhibit the same pattern as the previous measures of relative mobility. Emigrating sons show a lower intergenerational correlation indicating a higher level of social mobility than stayers. As with all of the previous measures, there are differences in the level of implied social mobility by host continent of the son. Irrespective of the host, all father-son pairs of geographically mobile sons exhibit higher social mobility with respect to the standardized HISCAM than father-son pairs of the baseline sample.[27]

Overall, the analysis of geographic mobility can be boiled down to three observations. First, there was selection of (temporary) international migrants with respect to the occupational category of the father and the son. Fathers of geographically mobile sons exhibited higher socioeconomic positions than those of geographically immobile, while these migrating sons tended to attain intermediate socioeconomic positions more often than geographically immobile. Second, this selection translates into different levels of intergenerational mobility. Across most measures, geographically immobile sons exhibited significantly lower levels of intergenerational mobility. Third, there are differences in both selection and the implied level of social mobility across destination continents. Migrants within Europe tended to be better situated than e.g. migrants to North America. Moreover, the former experienced more upward mobility than the latter. The evidence on the direction of differences in overall intergenerational mobility across host continents is inconclusive.

3.3.2 Life Pattern

Distribution across Occupational Categories Table 3.4 highlights that of originally 11,384 father-son pairs merely 13 percent remain in the life pattern sample. This means that only 1,476 father-son pairs feature categorizable observations of sons around the age of twenty, thirty, and forty and categorizable observations of fathers around the age of thirty, forty, and fifty. This is caused by timely death[28], naturalization after a certain

[27]The difference is not statistically significant for sons relocating to South America, Africa, Asia, or Australia.

[28]The average age at death was fifty-eight in the Zurich data.

age[29], and gaps in the observation years. The remaining father-son pairs are positively selected as their SEPs are, on average, higher than in the baseline sample.[30] Table 3.4 further shows that the fraction of middle SEP, high SEP, and (higher) white-collar individuals increased with age whereas the share of low SEP and (un)skilled individuals decreased with age. This upward intragenerational mobility seems natural as careers usually start at a lower socioeconomic position than they end. Further analyses are required to evaluate whether sample selection with respect to the age is a concern when estimating occupational mobility.

Absolute Mobility I start the analysis of life-cycle patterns in social mobility estimates with a measure of absolute mobility. The shares of (upward and downward) mobile individuals according to all classifications are presented in Figures 3.11, 3.12, and 3.13. Overall, there are differences in the estimates on the share of mobile ranging from 42 percent to 46 percent in the SEP categorization and from 31 (51) to 34 (54) percent in the (extended) Long-Ferrie categorization. Nevertheless, the evidence on the direction of the bias due to different ages at categorization of both the father and the son is inconclusive. On average, a higher age at classification of the son induces larger estimates of social mobility in the SEP classification. The Long-Ferrie categorizations do not exhibit such a monotone trend. With respect to the father's age at classification, the Long-Ferrie categorizations suggest (weakly) decreasing mobility whereas the SEP categorization does not feature a monotone trend. Not surprisingly, the prevalence of upward and downward mobility exhibits the same trend across all categorizations. The age of the father negatively (positively) correlates with upward (downward) mobility. The reverse is true for son's age at classification. This finding is predominantly caused by individuals exhibiting upward intragenerational mobility as is depicted in Table 3.4. If a father is ranked in a "higher" situated occupational category when he is older, the son is less likely to experience upward mobility with respect to that position himself. Similarly, if a sons have, on average, a lower socioeconomic position at lower ages, they are less likely to have already entered an occupation that is "higher" ranked than the one of their fathers. In summary,

[29]If an individual acquires the citizenship of Zurich after the age of e.g. thirty-five, there is no information on occupations at earlier ages, i.e. around thirty.

[30]This is partially caused by lower ages at death of lower SEP individuals. The average age at death for individuals with low, middle, and high SEP as highest occupational outcome was fifty-seven, fifty-nine, and sixty-two, respectively.

there are differences in the estimates of absolute intergenerational mobility. Evidence on the direction depending on the age of both the father and the son is mixed.

Relative Mobility Similar to the results on absolute mobility, the measures of relative mobility do not show a conclusive trend with respect to the age at classification of the father or the son. Even though the two-way log-odds ratios in Figures 3.14–3.16 exhibit fluctuations, they do not agree on a clear pattern with respect to categorization ages. The SEP categorization suggests that the classification age of the father affects mobility estimates in a u-shaped way if sons are classified around thirty or forty and in a positive way if sons are classified around twenty. This pattern is not mirrored in the Long-Ferrie categorizations. The Long-Ferrie categorizations do not even exhibit a homogeneous pattern with respect to the father's classification age across occupational categories. If anything, they propose that sons that are categorized at younger ages exhibit lower levels of occupational mobility. Apart from these observations, there is no monotone or homogeneous pattern observable with respect to the ages at classification.

The Altham statistics do not exhibit strong trends either (see Figures 3.17–3.19).[31] The Altham statistic of the SEP categorization suggests that mobility was lowest if the sons are classified around 40 and highest if the sons are classified around 20. The point estimates diverge more with higher ages at classification of the father. However, these differences are statistically insignificant. The Long-Ferrie categorizations indicate only a small effect of the age at classification of both the father and the son. All in all, measures of relative mobility indicate that the age at classification may affect the point estimate of intergenerational mobility estimates, but they do not exhibit a clear trend in the direction of the deviations.

Correlation Coefficient Interestingly, the correlation coefficient of the standardized HISCAM measure depicts (insignificant) trends in both father's and son's age at classification. Figure 3.20 hints at a negative correlation of intergenerational mobility with both the father's and the son's categorization age.[32] There are several potential explanations for these patterns. First, occupations at later ages might be more representative of the lifetime occupational potential. This explanation would imply that life-cycle bias

[31] Estimates of the uncontrolled Altham statistics are presented in Figures 3B.4–3B.6 in Appendix 3B

[32] The trend in the son's age at classification mirrors the trend suggested by the SEP-based Altham statistic.

might, in fact, be a concern when estimating occupational mobility with the HISCAM correlation coefficient. Second, the older the father at the age of classification the closer the son was to an actual occupational choice. Whether this choice was made by him (positively influenced by father) or arranged by the father could not be investigated with the data at hand. Third, the older the son the more likely the father was to be deceased. Consequently, especially sons of self-employed fathers might have inherited the father's business. All of these hypotheses are possible explanations for the observed trends but cannot be tested with the data at hand. Furthermore, the correlation coefficient is the only measure of occupational mobility exhibiting such clear and monotone trends with respect to the classification ages. Hence, the evidence on the direction of bias due to life-cycle patterns is inconclusive.

3.3.3 Linking Procedures

Performance and Distribution across Occupational Categories In this section, I present the results from applying automated linking procedures to the artificially separated father-son data. Table 3.7 contains an evaluation of the linking procedures. The match rates are very high at between 77 and 95 percent correct matches. Similarly, the share of type I errors (wrongly linked father-son pairs) is negligible with values below three per mille. The procedure of Ferrie (1996) produces marginally higher rates of type I errors and does not exhibit strong differences across phonetic name cleaning methods. The highest match rate both with respect to total and correct matches and lowest rate of type I error is achieved with the procedure by Abramitzky et al. (2012, 2014) with Soundex name cleaning. Not surprisingly, Bailey et al. (2019) find much higher error rates. Their estimates for the match rate (1 − type II error rate) lie between 20 and 40 percent for the same procedures. Similarly, they find a share of type I errors (false positives) between 22 and 43 percent. This depicts nicely that the sample I employ in this paper is not representative as the pool for potential matches is small and easily separable with respect to the linking characteristics (name, year of birth, place of origin).[33] Consequently, the conclusions from this paper can only be extended to the performance of linking mechanisms in data with similar quality and quantity. Still, it is interesting to gain

[33] In other words, there have to be two individuals in the pool of potential son matches with very similar names, year of birth, and exact same place of family origin to induce type I and II errors. As there is no misspelling in names nor errors in the year of birth, the automated linking procedures perform neatly.

first insights into performance differences when several linking procedures are employed to such detailed ground truth data.[34]

Tables 3.5 and 3.6 show that the high match rates and small fraction of false links translate into small differences with respect to the distribution across occupational categories and average age. Apparently, middle SEP and (lower) white-collar individuals were more likely to be matched both among fathers and sons. This skews the occupational distribution marginally in that direction. Similarly, younger individuals were matched more frequently. Nevertheless, the deviations are minimal (especially compared to the results from Bailey et al., 2019). Based on these findings, one would not expect that any of the intergenerational mobility estimates is significantly biased in the linked samples.

Estimates of Intergenerational Mobility As the solid performance of all automated linking procedures suggests, none of the measures of absolute and relative mobility exhibit large nor significant bias as compared to the baseline sample. Interestingly, employing Ferrie (1996) without name cleaning gets closest to the baseline sample with respect to mobility estimates even though it is outperformed with respect to match rates and false matches by Abramitzky et al. (2012, 2014) with Soundex name cleaning. Figures 3.21, 3.22, and 3.23 show that the share of mobile individuals is stable across mechanisms. There are minor differences with respect to the prevalence of upward vs downward mobility. The linked samples are somewhat more likely to contain upward mobile father-son pairs.

The two-way log-odds ratios depicted in Figures 3.24–3.26 point out minor differences too. Most linking mechanisms estimate higher log-odds ratios for the groups of high SEP and unskilled workers, whereas they estimate lower odds ratios for skilled workers and the lower white-collar group. Again, these differences are small. For example, the baseline estimate suggests that sons of high SEP fathers were 5.20 times more likely to enter the same occupational category vs another category than sons of low or middle SEP fathers. The corresponding estimate in the Abramitzky (NYSIIS) sample lies close at 5.45. Aggregating all log-odds ratios into the Altham statistic does not change the picture. Figures 3.27–3.29 depict that the point estimates vary somewhat but are always close to

[34] In this paper, I do not artificially impair the data to analyze the effect on performance as any impariment would induce the data to be simulated. This would undermine the motivation to evaluate linking procedures with the high-quality Zuirch data with observable father-son pairs.

the baseline estimate.[35] The occupational categorizations do not agree with respect to the direction of the bias based on the point estimates. The SEP categorization and the extended Long-Ferrie classification imply that linked samples marginally underestimate mobility whereas the three-category Long-Ferrie classification points towards overestimation of mobility in linked samples. Finally, the HISCAM correlation coefficient (Figure 3.30) further solidifies the impression that the employed linking procedures do not lead to significantly biased estimates of intergenerational mobility in the data at hand as the point estimates are virtually the same across all samples.

3.3.4 Relative Size of Bias

In this section, I evaluate the relative size of bias due to the three different sources. The previous sections have already lined out that one should expect migration to have the largest or at least most consistent impact. The expectation on the impact of different classification ages is unclear whereas automated linking procedures should not exhibit relatively large deviations. Tables 3.8, 3.9, and 3.10 display the direction of the bias due to each source and the relative size in percent of the baseline sample's estimate for all of the employed measures of intergenerational mobility. Figure 3.31 depicts the results for the correlation coefficient based on HISCAM to provide a representative graphical illustration. In order to boil down the results from the previous sections, I only present the bias in selected sub-samples. Namely, I compare all estimates of six samples: (1) the baseline sample including all father-son pairs, (2) the sample with geographically immobile sons[36], (3) the linked sample employing the procedure of Ferrie (1996) without name cleaning, and (4)–(6) three combinations of father's and son's age at classification (son at twenty and father at fifty (4), both at forty (5), and son at forty and father at thirty (6)). Note that the estimated level of mobility in the last three sub-samples are not as easily comparable to the baseline sample as the former two. Of course, one can see which of the selected ages produce estimates closest to the baseline sample but I excluded all father-son pairs that were not observable at all ages in these sub-samples. Consequently, comparing the three with each other gives better insights in the relative size of the bias.

[35] The uncontrolled Altham statistics are presented in Appendix 3B (Figures 3B.7–3B.9).

[36] This poses as direct comparison to the most prevalent scenario in the existing literature on social mobility, as most analyses are restricted to the non-migrating population.

The results suggest that restricting the sample to geographically immobile individuals consistently biases the estimate of intergenerational mobility downwards by between 1 and 10 percent. The bias due to employing linking procedures is comparably negligible. It is between four and eighty-five times smaller than the migration bias and never exceeds 1 percent of the baseline estimate. The life pattern estimates differ substantially from the baseline sample as well. These differences between the life pattern samples and the baseline sample are both due to sample selection (excluding all individuals not observable at every age) and differences in the level of social mobility caused by differences in age. Consequently, the comparison with the other sources of bias is to be taken with a grain of salt. Comparing the three life pattern samples among each other seems more appropriate. This comparison reveals that the deviations between the three samples' estimates usually range up to 10 percent of the baseline sample. This suggests that the relative size of bias due to life patterns may be roughly comparable to the relative size of migration bias. However, there is no apparent ordering of the three classification age combinations across different occupational categorizations or measures of mobility.

All in all, the results on bias due to each of the three sources can be summarized as follows. Firstly, narrowing the analysis down to geographically immobile individuals underestimates the level of intergenerational mobility with deviations between 1 and 10 percent (depending on the measure of mobility). Secondly, life patterns or the age at classification affect the estimated level of occupational mobility but the results are inconclusive with respect to trends, direction, and relative size of the bias. Thirdly, automated linking procedures do not generate significant bias in social mobility estimates in the data base of Zurich's male citizenry in the nineteenth century.

3.4 Conclusion

This paper contributes to several strands of the literature related to the topic of intergenerational mobility such as migration, life-cycle bias, and record linkage by employing data on Zurich's citizenry between 1799 and 1926. The data are unique because they contain observable intergenerational links, and allow to track individuals over the course of their lives and to follow them after emigration. These features enable me to evaluate potential biases in estimates of social mobility. I explore the direction and size of distortions due to the following sources: (1) migration, (2) life-cycle patterns in occupational outcomes, and

(3) record linkage. Each bias can be set into relation in order to highlight where future research has to be particularly careful. In addition, the analysis is based on a broad set of measures for absolute and relative occupational mobility.

The results can be boiled down to four main findings. First, emigrants were intermediately selected with differences by country of destination. Zurich emigrants to European countries were more positively selected as compared to emigrants to the United States and Canada in the nineteenth century. Second, Zurich citizens exhibited an occupational life pattern indicating that individuals experienced non-negligible levels of intragenerational (upward) mobility. The older a male citizen was the higher his socioeconomic position. Third, state-of-the-art record linkage procedures perform well due to the detail of information and the small size of the populations to match. On average, around 85 percent of father-son pairs could be matched and less than three per mille of matches were wrongly assigned. Fourth, excluding emigrating individuals underestimates the level of social mobility of all father-son pairs by an average of 4 percent. Life patterns in the occupational distribution affect estimates of intergenerational mobility on a comparable scale but do not exhibit a monotone pattern with respect to age of the father or the son. Due to their neat performance, linking procedures do not induce social mobility estimates to deviate significantly from "true" estimates in non-linked data. Consequently, future research should aim at addressing all of the raised issues depending on the quality and number of the data at hand.

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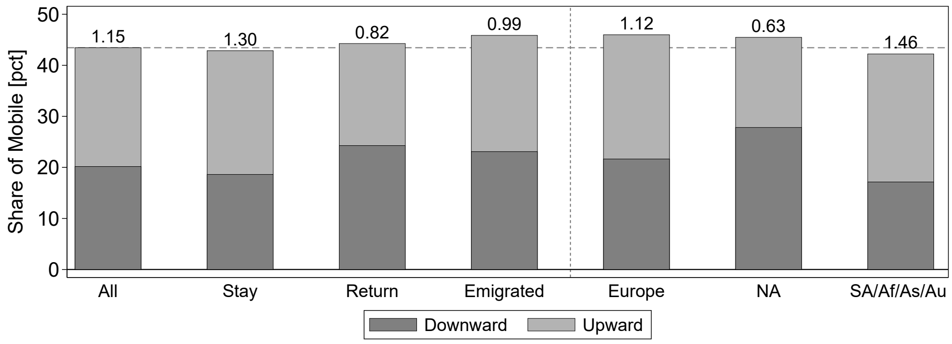
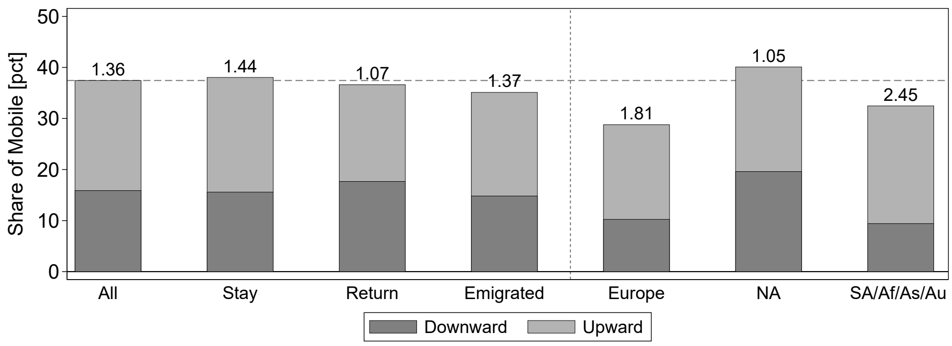
Figures and Tables

FIGURE 3.1. SHARE OF (UPWARD AND DOWNWARD) MOBILE ACCORDING TO SEP CATEGORIES BY MIGRATION STATUS.



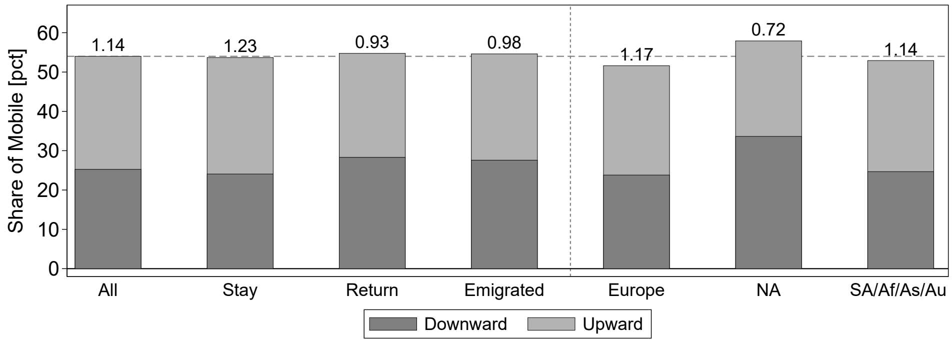
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobile individuals enter higher SEP than their father. The numbers above the bars denote the ratio of upward to downward mobility. The dashed horizontal line marks the share of mobile in the baseline sample (All). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

FIGURE 3.2. SHARE OF (UPWARD AND DOWNWARD) MOBILE ACCORDING TO LONG-FERRIE CATEGORIES BY MIGRATION STATUS.



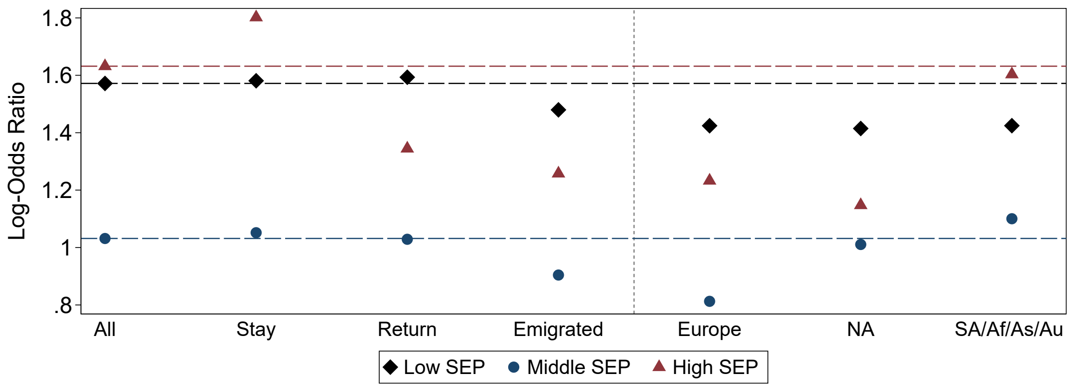
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to white-collar occupations. The numbers above the bars denote the ratio of upward to downward mobility. The dashed horizontal line marks the share of mobile in the baseline sample (All). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.3. Share of (upward and downward) mobile according to extended Long-Ferrie categories by migration status.



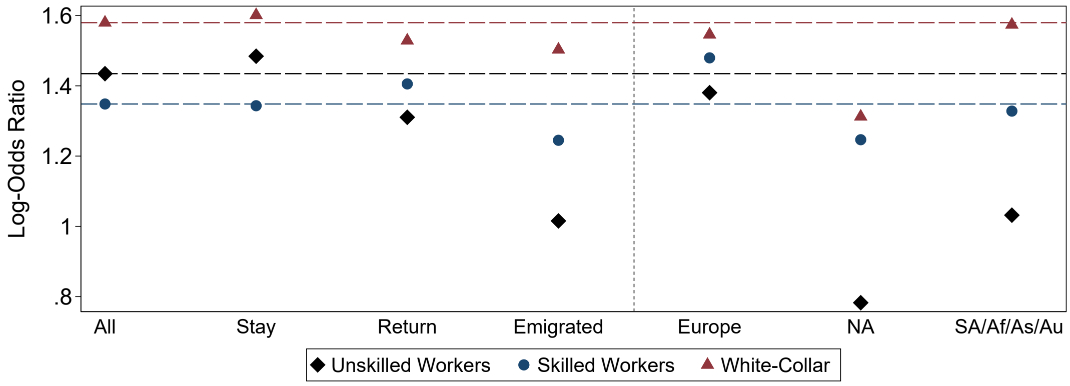
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to higher white-collar occupations. The numbers above the bars denote the ratio of upward to downward mobility. The dashed horizontal line marks the share of mobile in the baseline sample (All). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.4. Two-way log-odds ratios according to SEP categories by migration status.



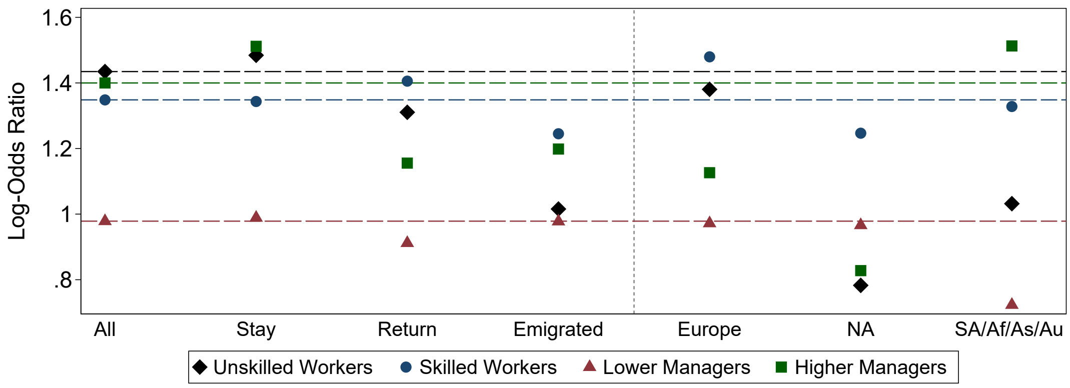
Note: The dashed lines denote the levels of the log-odds ratios in the baseline sample (All, color-coded). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

FIGURE 3.5. TWO-WAY LOG-ODDS RATIOS ACCORDING TO LONG-FERRIE CATEGORIES BY MIGRATION STATUS.



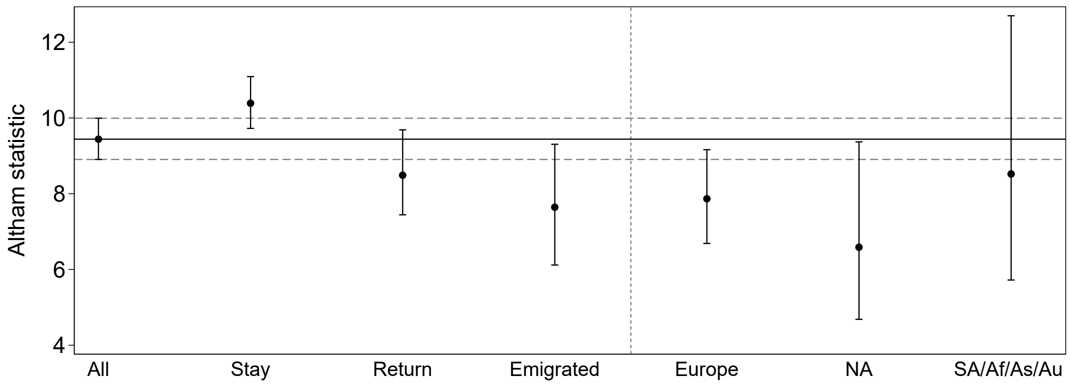
Note: The dashed lines denote the levels of the log-odds ratios in the baseline sample (All, color-coded). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

FIGURE 3.6. TWO-WAY LOG-ODDS RATIOS ACCORDING TO EXTENDED LONG-FERRIE CATEGORIES BY MIGRATION STATUS.



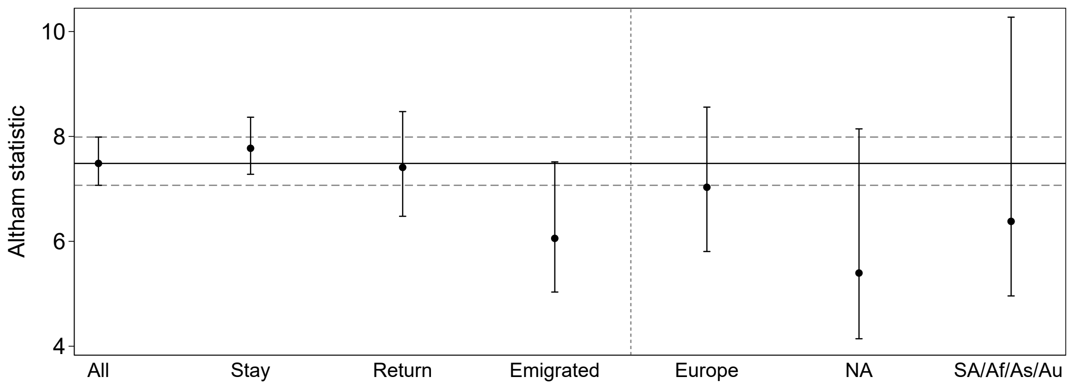
Note: The dashed lines denote the levels of the log-odds ratios in the baseline sample (All, color-coded). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.7. Altham statistic according to SEP categories by migration status.



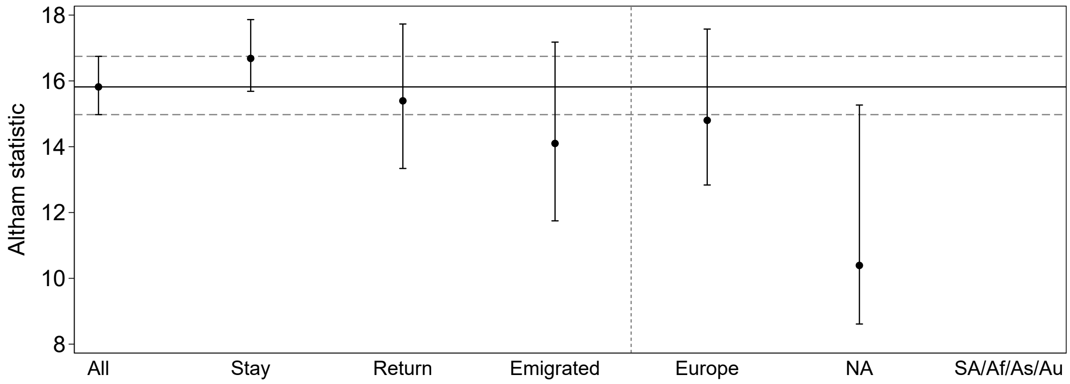
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.8. Altham statistic according to Long-Ferrie categories by migration status.



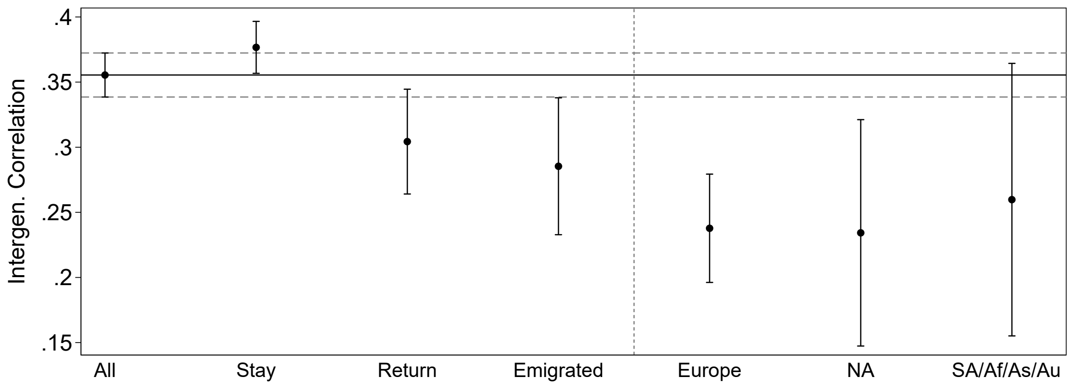
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.9. Altham statistic according to extended Long-Ferrie categories by migration status.



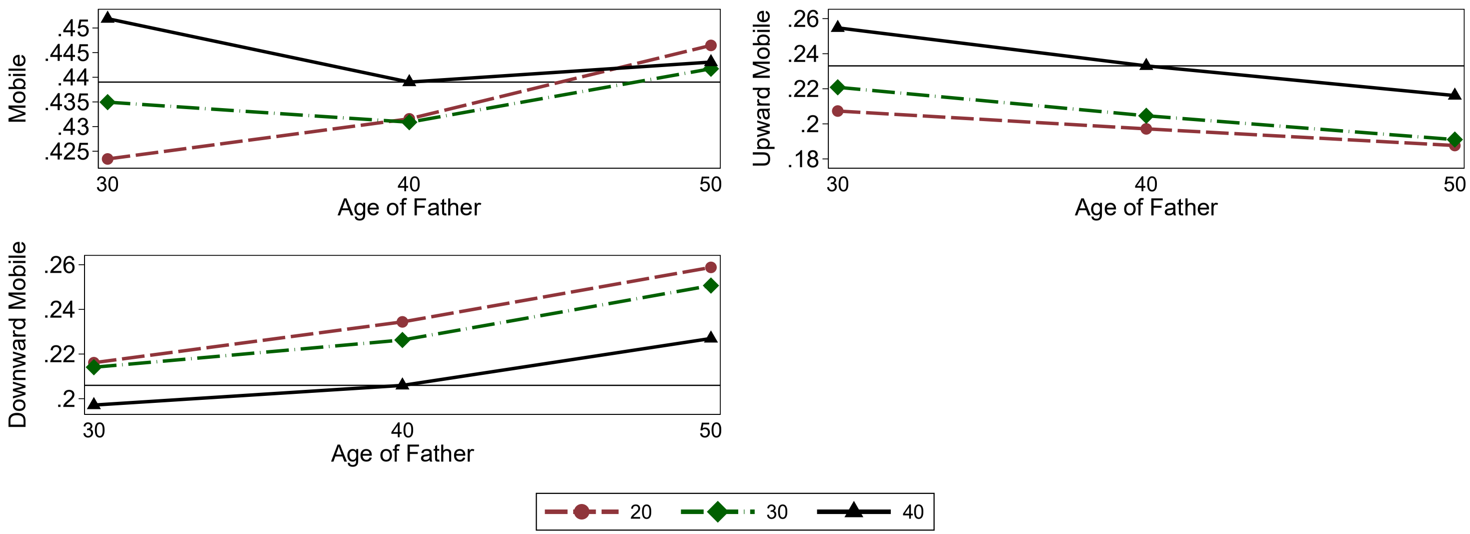
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.10. Correlation coefficient of the standardized HISCAM measure by migration status.



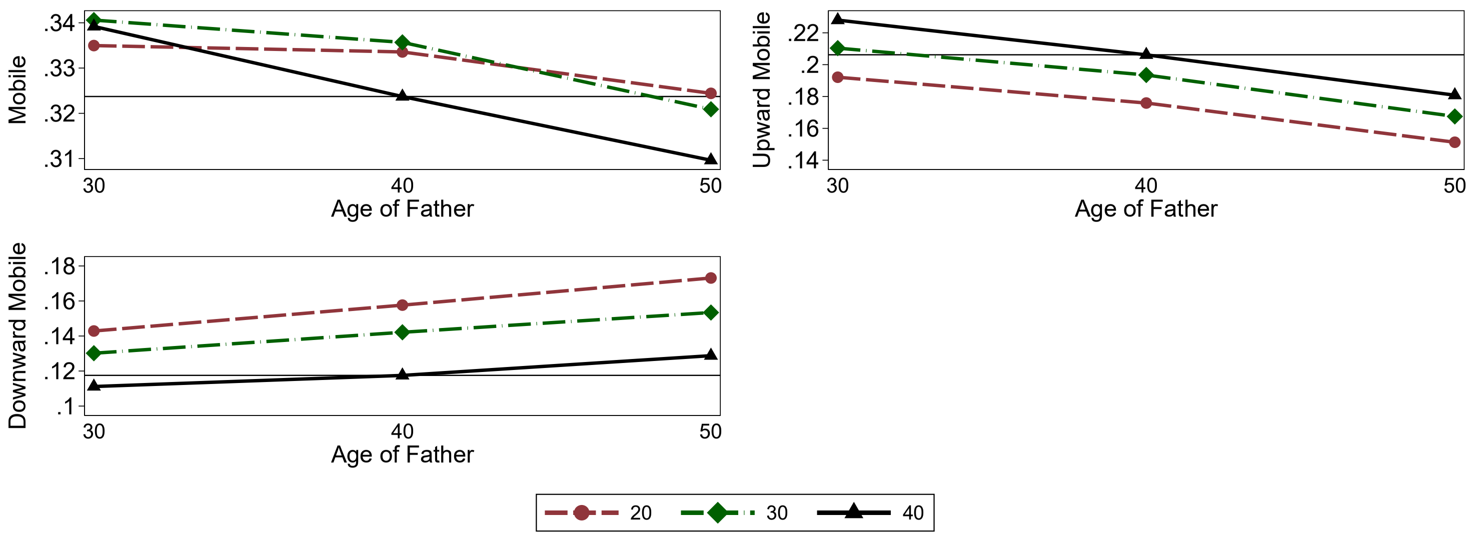
Note: The solid (dashed) horizontal line represents the estimate (confidence intervals) for the baseline sample (All). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3.11. Share of (upward and downward) mobile according to SEP categories by age at classification.



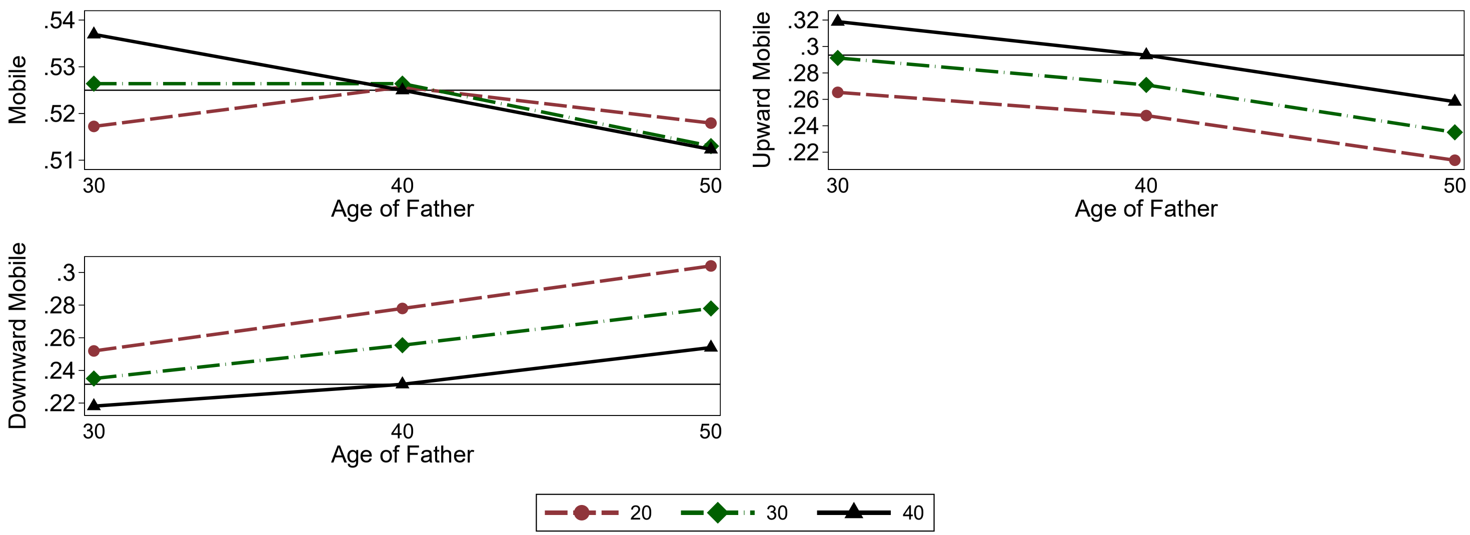
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. The share of mobile denotes sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobile individuals enter higher SEP than their father. The horizontal line marks the share of mobile of the 40-40 sample (both son and father categorized at age 40).

Figure 3.12. Share of (upward and downward) mobile according to Long-Ferrie categories by age at classification.



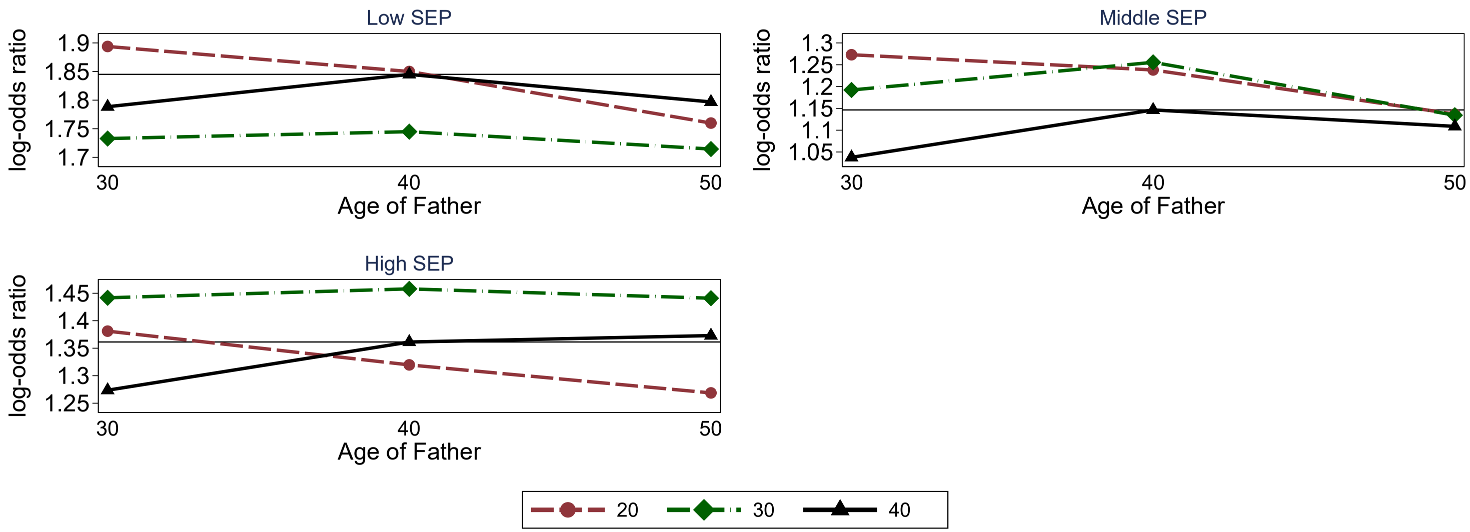
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. The share of mobile denotes sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to white-collar occupations. The horizontal line marks the share of mobile of the 40-40 sample (both son and father categorized at age 40).

Figure 3.13. Share of (upward and downward) mobile according to extended Long-Ferrie categories by age at classification.



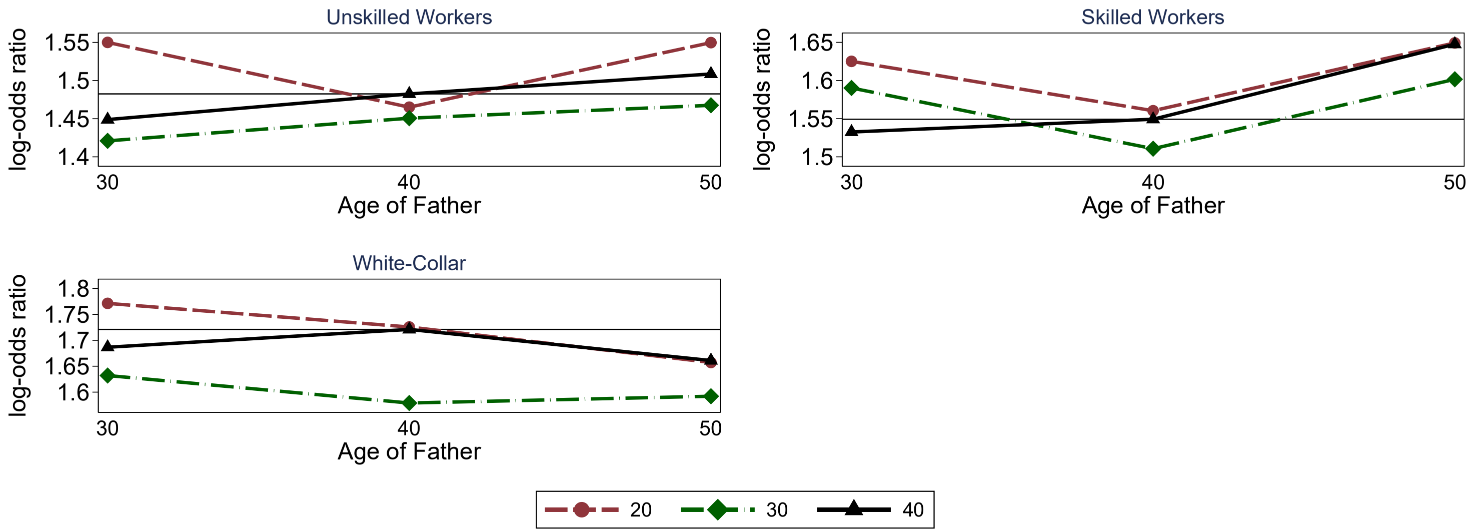
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. The share of mobile denotes sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to higher white-collar occupations. The horizontal line marks the share of mobile of the 40-40 sample (both son and father categorized at age 40).

FIGURE 3.14. TWO-WAY LOG-ODDS RATIOS ACCORDING TO SEP CATEGORIES BY AGE AT CLASSIFICATION.



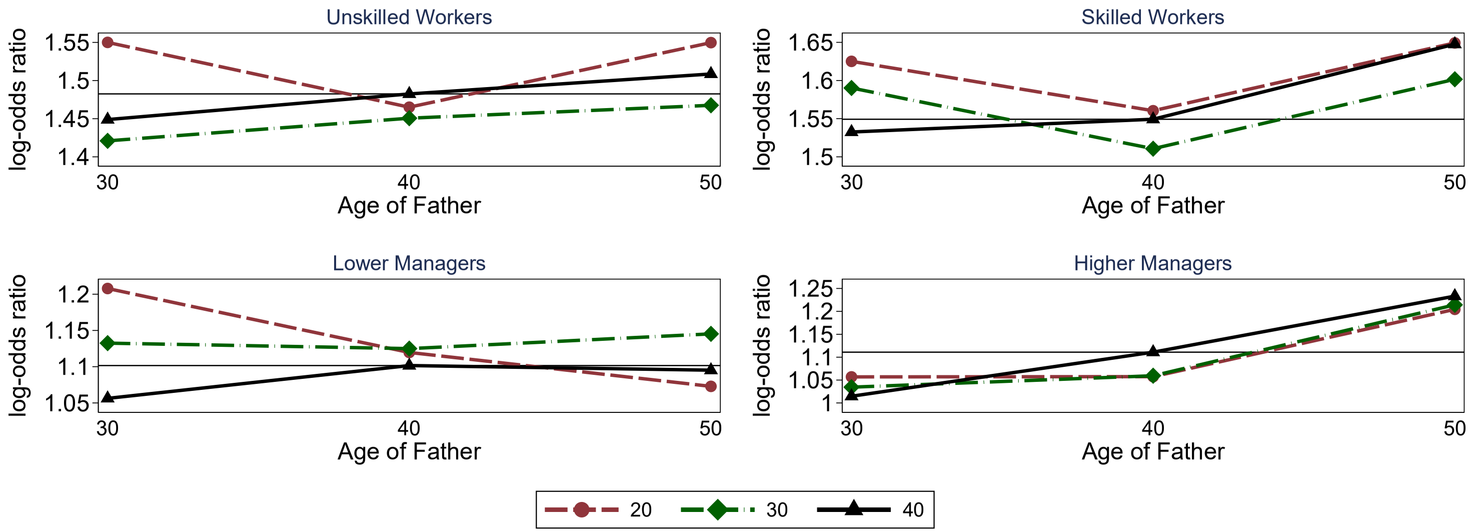
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. The horizontal lines denote the level of the log-odds ratios of the 40-40 sample (both son and father categorized at age 40).

Figure 3.15. Two-way log-odds ratios according to Long-Ferrie categories by age at classification.



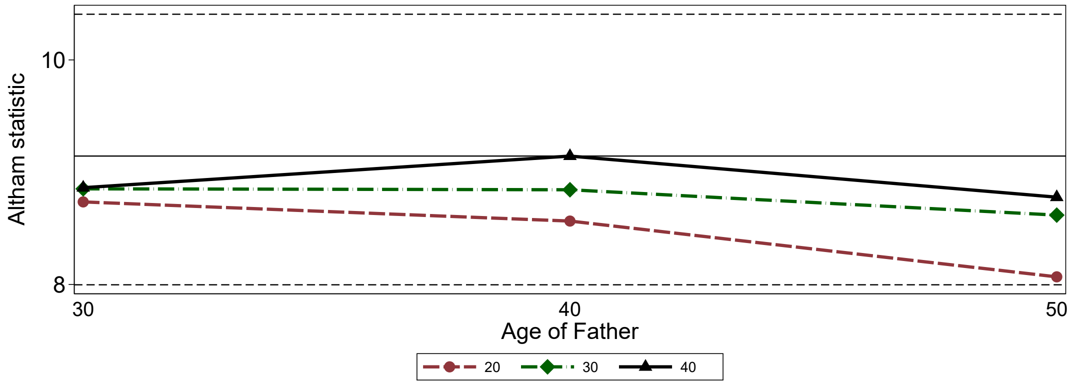
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. The horizontal lines denote the level of the log-odds ratios of the 40-40 sample (both son and father categorized at age 40).

Figure 3.16. Two-way log-odds ratios according to extended Long-Ferrie categories by age at classification.



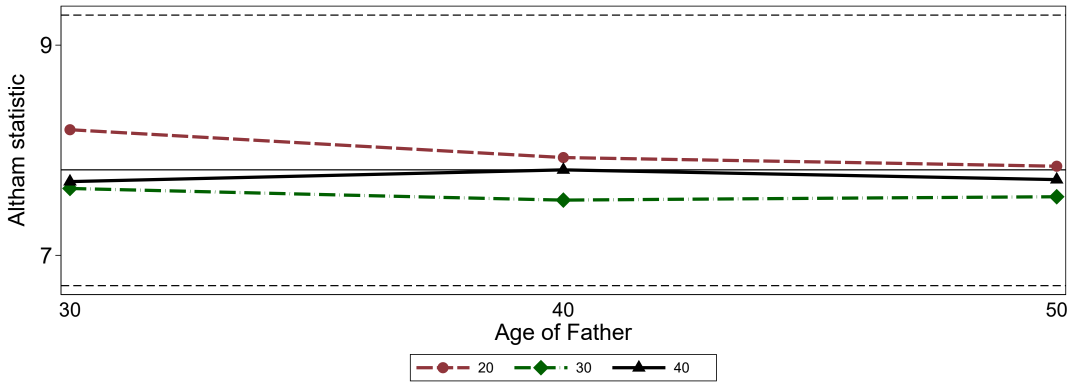
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. The horizontal lines denote the level of the log-odds ratios of the 40-40 sample (both son and father categorized at age 40).

Figure 3.17. Altham statistic according to SEP categories by age at classification.



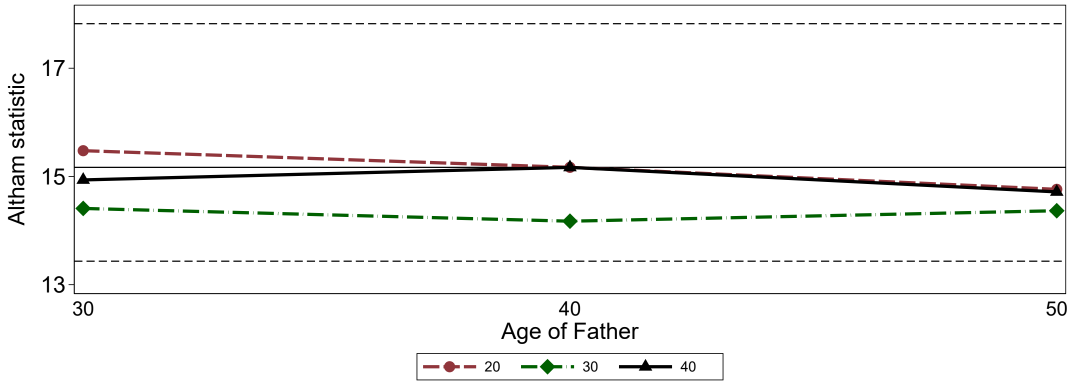
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.18. Altham statistic according to Long-Ferrie categories by age at classification.



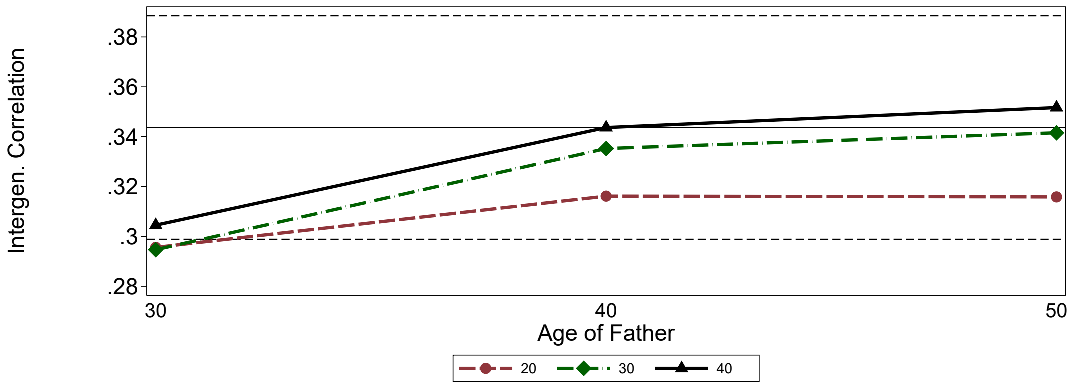
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.19. Altham statistic according to extended Long-Ferrie categories by age at classification.



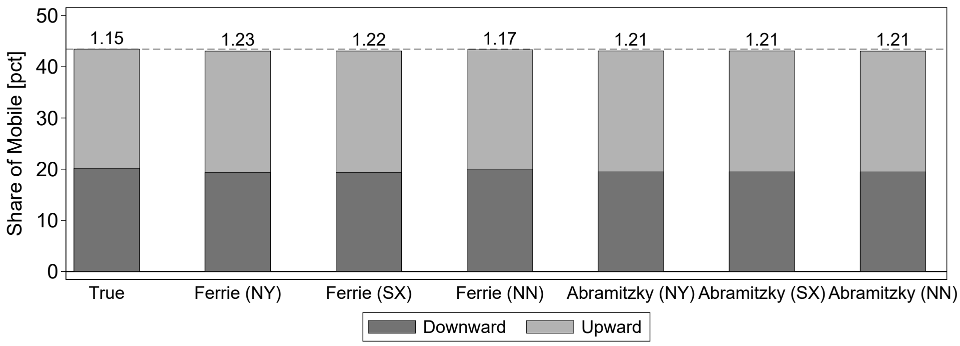
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.20. Correlation coefficient of the standardized HISCAM measure by age at classification.



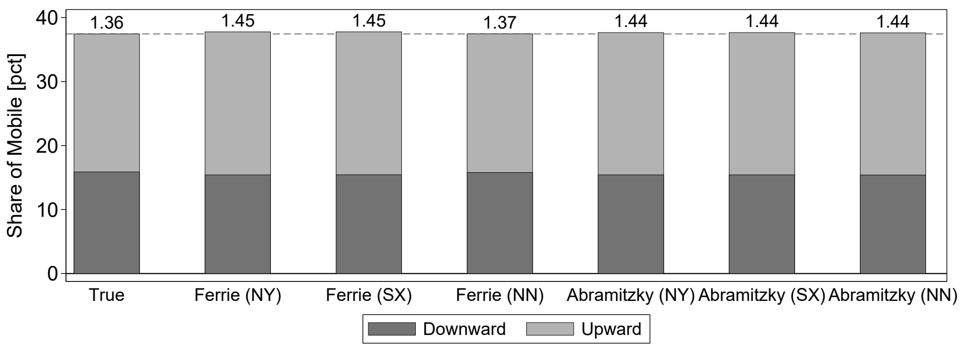
Note: The age at classification of the son is color coded, the father's age at classification is on the x-axis. The solid (dashed) horizontal line represents the estimate (confidence intervals) of the 40-40 sample (both son and father categorized at age 40).

Figure 3.21. Share of (upward and downward) mobile according to SEP categories by linking procedure.



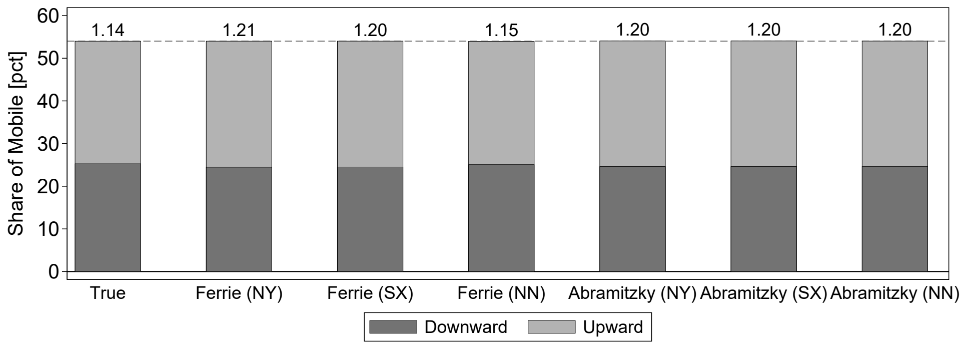
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobile individuals enter higher SEP than their father. The numbers above the bars denote the ratio of upward to downward mobility. The horizontal line marks the share of mobile in the baseline sample (True).

Figure 3.22. Share of (upward and downward) mobile according to Long-Ferrie categories by linking procedure.



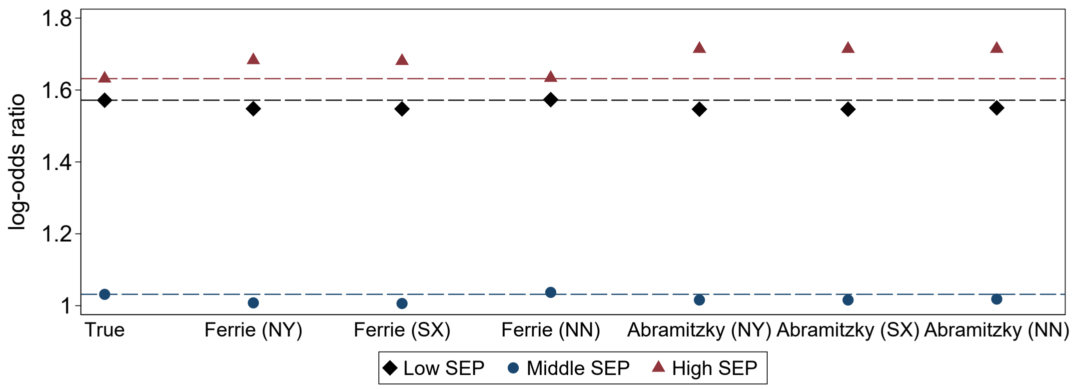
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to white-collar occupations. The numbers above the bars denote the ratio of upward to downward mobility. The horizontal line marks the share of mobile in the baseline sample (True).

Figure 3.23. Share of (upward and downward) mobile according to extended Long-Ferrie categories by linking procedure.



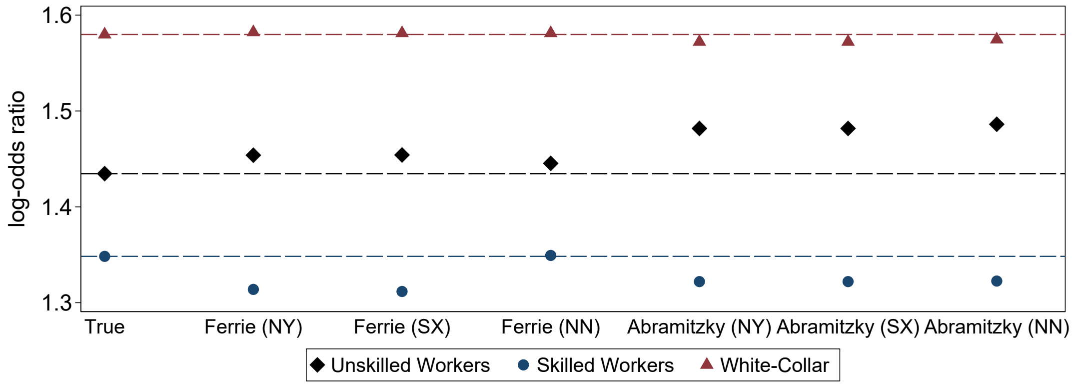
Note: The height of the bars displays the share of mobile sons that did not enter the same occupational category as their father (off-diagonal in the transition matrices). Upward mobility denotes individuals that move closer to higher white-collar occupations. The numbers above the bars denote the ratio of upward to downward mobility. The horizontal line marks the share of mobile in the baseline sample (True).

Figure 3.24. Two-way log-odds ratios according to SEP categories by linking procedure.



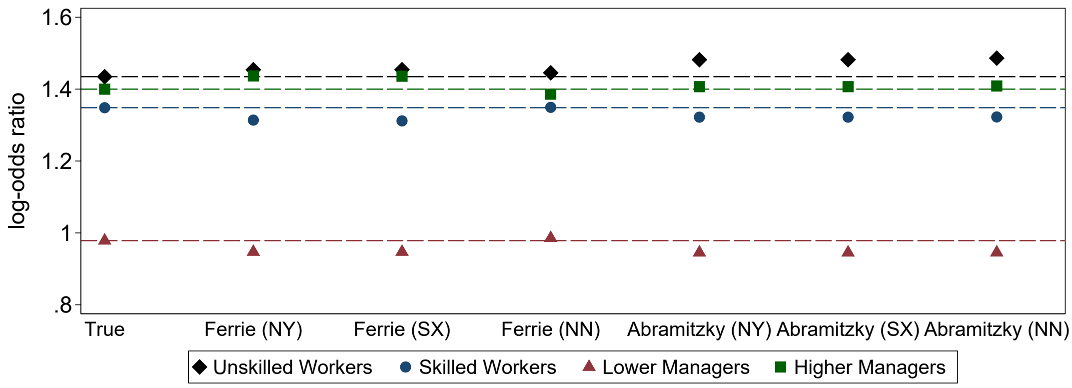
Note: The dashed lines denote the level of the log-odds ratios in the baseline sample (color-coded, True).

Figure 3.25. Two-way log-odds ratios according to Long-Ferrie categories by linking procedure.



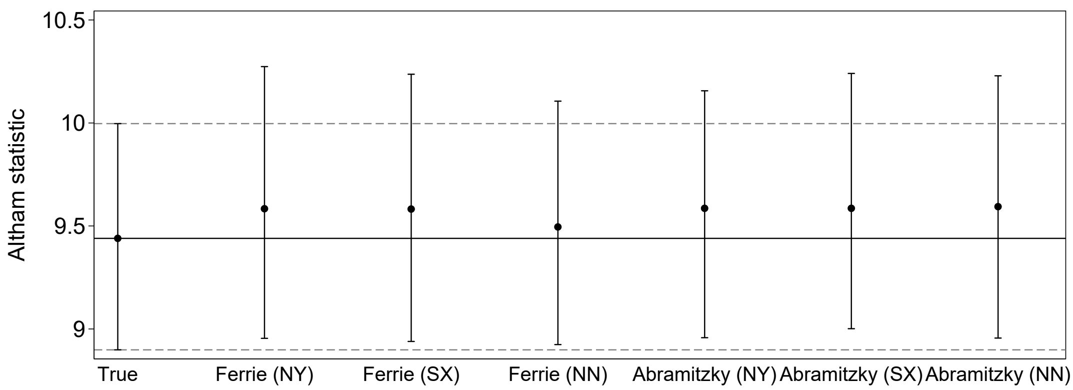
Note: The dashed lines denote the level of the log-odds ratios in the baseline sample (color-coded, True).

Figure 3.26. Two-way log-odds ratios according to extended Long-Ferrie categories by linking procedure.



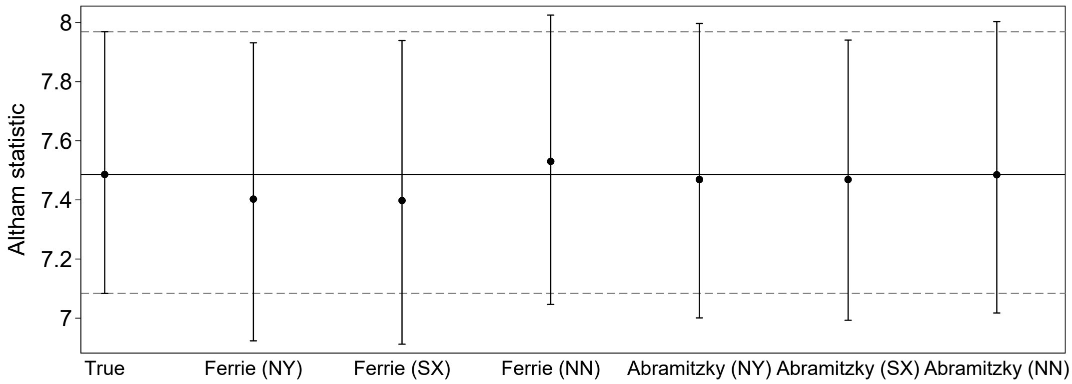
Note: The dashed lines denote the level of the log-odds ratios in the baseline sample (color-coded, True).

Figure 3.27. Altham statistic according to SEP categories by linking procedure.



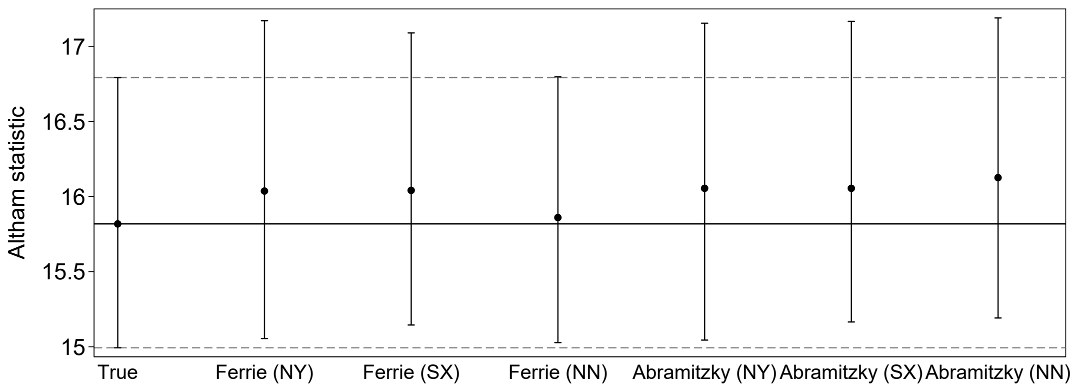
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.28. Altham statistic according to Long-Ferrie categories by linking procedure.



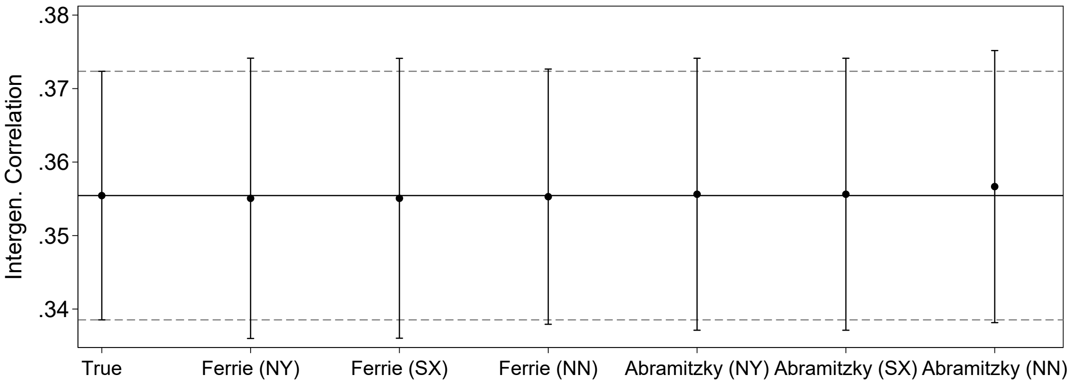
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.29. Altham statistic according to extended Long-Ferrie categories by linking procedure.



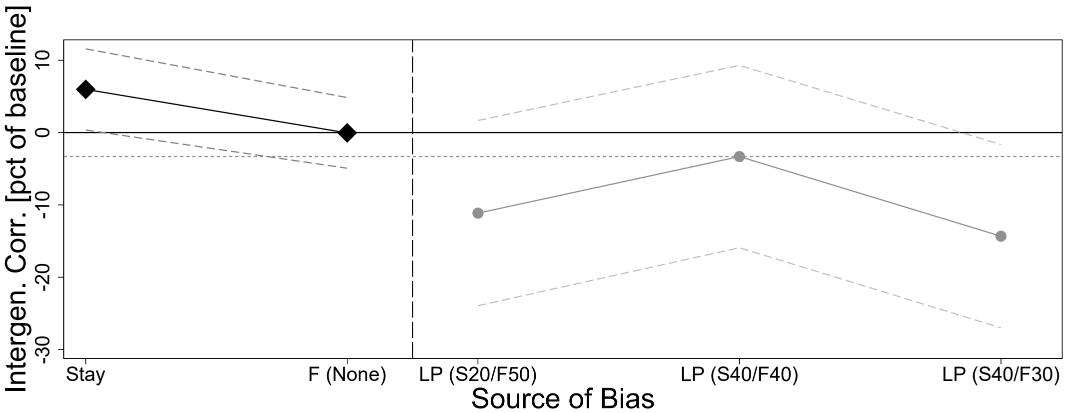
Note: This figure contains the Altham statistic controlled for a quadratic function of the father's and the son's age. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3.30. Correlation coefficient of the standardized HISCAM measure by linking procedure.



Note: The solid (dashed) horizontal line represents the estimate (confidence intervals) for the baseline sample ("True").

Figure 3.31. Relative size of bias with the standardized HISCAM measure.



Note: The solid horizontal line represents 0 percent bias (baseline sample). The vertical dashed line separates migration and linking procedure as sources of bias on the left-hand side from life pattern differences on the right-hand side. The dashed gray horizontal line marks the level of bias when only including father-son pairs within a five year range around the age of 40. Stay denotes the sample with geographically immobile sons. Ferrie (None) is the linked sample employing Ferrie (1996) without name cleaning. LP is short for life pattern. These samples include father-son pairs that contain information at every age between 20 and 40 (son) and 30 and 50 (father). LP (Sx/Fy) classifies the LP father-son pairs around the age of x (son) and y (father).

Table 3.1. Descriptive statistics of the baseline sample.

Characteristic	Son	Father
Number of observations	11,384	
Age	35.53	47.17
Low SEP [pct]	37.87	40.72
Middle SEP [pct]	46.56	42.33
High SEP [pct]	15.57	16.95
Unskilled workers [pct]	11.47	14.25
Skilled workers [pct]	24.40	25.39
White-collar [pct]	64.13	60.36
Lower managers [pct]	39.81	33.01
Higher managers [pct]	24.32	27.35

Note: The number of observations refers to the number of father-son pairs. Age is the age at observed occupation closest to forty. The remainder of the table describes the distribution across occupational classes in percent. Lower managers and higher managers are encompassed in the white-collar group.

Table 3.2. Descriptive statistics of father-son pairs by migration status.

Characteristic	Stay	Return	Emigrated
Number of observations	8,002	2,126	1,256
Age	35.25	37.21	34.60
Age at Migration		25.50	26.23
Low SEP [pct]	38.54	39.42	30.94
Middle SEP [pct]	44.93	46.84	56.56
High SEP [pct]	16.53	13.75	12.50
Unskilled workers [pct]	12.28	10.12	8.64
Skilled workers [pct]	24.41	26.80	20.23
White-collar [pct]	63.31	63.08	71.13
Lower managers [pct]	38.12	39.42	51.21
Higher managers [pct]	25.18	23.66	19.92
Age (f)	48.47	44.59	44.19
Low SEP [pct] (f)	42.42	37.27	35.31
Middle SEP [pct] (f)	41.81	43.18	44.33
High SEP [pct] (f)	15.77	19.55	20.36
Unskilled workers [pct] (f)	15.52	11.12	11.20
Skilled workers [pct] (f)	25.84	25.66	22.03
White-collar [pct] (f)	58.63	63.22	66.77
Lower managers [pct] (f)	32.23	33.71	36.87
Higher managers [pct] (f)	26.41	29.51	29.90

Note: The number of observations refers to the number of father-son pairs by migration status. Age is the age at observed occupation closest to forty. Age at Migration denotes the sons' age at first migration. The remainder of the table describes the distribution across occupational classes in percent. Lower managers and higher managers are encompassed in the white-collar group. Tables 3.3 and 3B.1 split the migrants by destination. Rows with an (f) capture the values for the fathers, those without an (f) capture the values for the sons.

Table 3.3. Descriptive statistics of father-son pairs by destination continent.

Characteristic	Europe	NA	SA/Af/As/Au
Number of observations	2,088	453	315
Age	36.46	36.44	35.23
Age at Migration	26.29	27.10	25.91
Low SEP [pct]	21.23	40.85	21.91
Middle SEP [pct]	61.59	51.49	69.14
High SEP [pct]	17.19	7.66	8.95
Unskilled workers [pct]	5.27	9.81	5.03
Skilled workers [pct]	14.36	29.21	14.47
White-collar [pct]	80.37	60.98	80.50
Lower managers [pct]	51.93	46.70	67.92
Higher managers [pct]	28.44	14.29	12.58
Age (f)	44.51	43.71	44.69
Low SEP [pct] (f)	27.70	38.40	34.12
Middle SEP [pct] (f)	49.63	41.91	49.26
High SEP [pct] (f)	22.68	19.69	16.62
Unskilled workers [pct] (f)	8.55	13.14	11.90
Skilled workers [pct] (f)	18.36	24.71	21.13
White-collar [pct] (f)	73.08	62.16	66.96
Lower managers [pct] (f)	39.53	32.75	40.77
Higher managers [pct] (f)	33.55	29.41	26.19

Note: The number of observations refers to the number of father-son pairs by destination continent. Note that one father-son pair may be included in more than one sub-sample because of multiple migration. Age is the age at observed occupation closest to forty. Age at Migration denotes the sons' age at first migration. The remainder of the table describes the distribution across occupational classes in percent. Lower managers and higher managers are encompassed in the white-collar group. Table 3B.1 splits the SA/Af/As/Au sample in separate parts (South America, Africa, Asia, and Australia). Rows with an (f) capture the values for the fathers, those without an (f) capture the values for the sons.

Table 3.4. Descriptive statistics by age at classification.

Characteristic	20	30	40	50
Number of ovservations		1,476		
Age	20.30	30.31	39.95	
Low SEP [pct]	36.86	32.99	28.66	
Middle SEP [pct]	44.38	50.75	53.12	
High SEP [pct]	18.77	16.26	18.22	
Unskilled workers [pct]	7.04	7.11	7.25	
Skilled workers [pct]	28.22	24.07	19.63	
White-collar [pct]	64.74	68.82	73.12	
Lower managers [pct]	42.22	42.93	44.26	
Higher managers [pct]	22.52	25.90	28.85	
Age (f)		30.60	40.29	50.01
Low SEP [pct] (f)		37.20	34.82	32.72
Middle SEP [pct] (f)		41.12	42.07	42.55
High SEP [pct] (f)		21.68	23.10	24.73
Unskilled workers [pct] (f)		10.27	9.22	7.53
Skilled workers [pct] (f)		27.73	25.97	24.77
White-collar [pct] (f)		62.00	64.81	67.70
Lower managers [pct] (f)		33.99	34.34	34.27
Higher managers [pct] (f)		28.01	30.47	33.43

Note: The numbers in the columns refer to the approximate age at which I classify the occupations of individuals. The number of observations refers to the number of father-son pairs. Age is the age at observed occupation closest to 20, 30, 40, or 50. The remainder of the table describes the distribution across occupational classes in percent. Lower managers and higher managers are encompassed in the white-collar group. Rows with an (f) capture the values for the fathers, those without an (f) capture the values for the sons.

Table 3.5. Descriptive statistics by linking mechanism.

Mechanism	Nobs	Gen	Age	L [pct]	M [pct]	H [pct]
Ferrie (NYSIIS)	9,492	Son	34.55	37.59	47.93	14.48
		Father	47.00	41.58	42.99	15.43
Ferrie (Soundex)	9,473	Son	34.54	37.55	47.94	14.50
		Father	47.00	41.56	43.00	15.44
Ferrie (None)	9,492	Son	34.55	37.59	47.93	14.48
		Father	47.00	41.58	42.99	15.43
Abramitzky (NYSIIS)	8,950	Son	34.21	37.74	48.22	14.05
		Father	47.10	41.85	43.30	14.85
Abramitzky (Soundex)	10,806	Son	35.42	37.87	46.78	15.36
		Father	47.08	40.97	42.38	16.65
Abramitzky (None)	8,979	Son	34.21	37.74	48.24	14.02
		Father	47.07	41.81	43.30	14.89

Note: Mechanism denotes the linking mechanism employed. The number of observations (Nobs) refers to the number of father-son pairs (matches). Gen refers to generation and denotes whether the captured values are for fathers or sons. Age is the age at observed occupation closest to forty. L, M, and H are the fraction of individuals with low, middle, and high SEP occupations, respectively. The distribution across Long-Ferrie categories is displayed in Table 3.6.

Table 3.6. Descriptive statistics by linking mechanism—distribution across Long-Ferrie categories.

Mechanism	Gen	U [pct]	S [pct]	W [pct]	LW [pct]	HW [pct]
Ferrie (NYSIIS)	Son	11.53	23.80	64.66	41.19	23.47
	Father	14.55	25.83	59.62	34.24	25.38
Ferrie (Soundex)	Son	11.54	23.74	64.72	41.23	23.48
	Father	14.55	25.77	59.67	34.27	25.40
Ferrie (None)	Son	11.53	23.80	64.66	41.19	23.47
	Father	14.55	25.83	59.62	34.24	25.38
Abramitzky (NYSIIS)	Son	11.53	23.86	64.61	41.39	23.22
	Father	14.70	25.87	59.44	34.48	24.96
Abramitzky (Soundex)	Son	11.53	24.24	64.24	40.03	24.21
	Father	14.34	25.46	60.20	33.33	26.87
Abramitzky (None)	Son	11.54	23.84	64.62	41.41	23.21
	Father	14.67	25.86	59.48	34.47	25.00

Note: Mechanism denotes the linking mechanism employed. The number of observations and average age is displayed in Table 3.5. Gen refers to generation and denotes whether the captured values are for fathers or sons. U, S, W, LW, and HW are the fraction of individuals in the occupational group of unskilled workers, skilled workers, white-collar, lower managers, and higher managers.

TABLE 3.7. EVALUATION OF LINKING PROCEDURES.

Procedure	Nobs	Matches	Correct	Type I
Ferrie (NYSIIS)	12,791	10,551 (82.49)	10,548 (82.46)	2.84
Ferrie (Soundex)		10,526 (82.29)	10,523 (82.27)	2.85
Ferrie (None)		10,551 (82.49)	10,548 (82.46)	2.84
Abramitzky (NYSIIS)		9,922 (77.57)	9,920 (77.55)	2.02
Abramitzky (Soundex)		12,082 (94.46)	12,080 (94.44)	1.66
Abramitzky (None)		9,955 (77.83)	9,953 (77.81)	2.01

Note: Procedure denotes the linking mechanism employed. Nobs denotes the number of observations in the baseline sample (without excluding farmers). Matches is the absolute number of matched father-son pairs (share of total observations [pct] in brackets). Correct is the absolute number of correct matches (share of total observations [pct] in brackets corresponding to 1 – type II error rate). Type I is the share of type I errors per mille.

TABLE 3.8. RELATIVE SIZE OF BIAS—SEP CLASSIFICATION.

Sample	M	IC	AS	$\Theta_{2,1}$	$\Theta_{2,2}$	$\Theta_{2,3}$
Baseline	0.43	0.36	9.44	1.57	1.03	1.63
Stay	-1.37	5.97	10.05	0.59	1.95	10.42
Ferrie (None)	-0.27	-0.04	0.59	0.10	0.53	0.12
LP (S20/F50)	2.76	-11.14	-14.53	11.98	10.20	-22.24
LP (S40/F40)	1.05	-3.31	-3.14	17.39	11.13	-16.57
LP (S40/F30)	4.01	-14.32	-6.12	13.80	0.59	-21.95

Note: Baseline marks the estimates of the mobility measures in the baseline sample. Stay denotes the sample of geographically immobile sons. Ferrie (None) is the linked sample employing Ferrie (1996) without name cleaning. LP is short for life pattern. These samples include father-son pairs that contain information at every age between 20 and 40 (son) and 30 and 50 (father). LP (Sx/Fy) classifies the LP father-son pairs around the age of x (son) and y (father). M is the share of mobile individuals, IC is the intergenerational correlation coefficient based on HISCAM, AS the controlled Altham statistic, and $\Theta_{2,x}$ the two-way log-odds ratio of category $x \in \{1, 2, 3\}$ corresponding to low, middle, and high SEP. The relative size of the deviation is denoted in percent of the baseline.

Table 3.9. Relative size of bias—Long-Ferrie classification.

Sample	M	IC	AS	$\Theta_{2,1}$	$\Theta_{2,2}$	$\Theta_{2,3}$
Baseline	0.37	0.36	7.49	1.43	1.35	1.58
Stay	1.59	5.97	3.85	3.46	-0.37	1.36
Ferrie (None)	0.05	-0.04	0.59	0.75	0.08	0.09
LP (S20/F50)	-13.35	-11.14	4.83	8.02	22.32	4.90
LP (S40/F40)	-13.54	-3.31	4.37	3.33	14.91	8.94
LP (S40/F30)	-9.41	-14.32	2.88	0.99	13.67	6.76

Note: Baseline marks the estimates of the mobility measures in the baseline sample. Stay denotes the sample of geographically immobile sons. Ferrie (None) is the linked sample employing Ferrie (1996) without name cleaning. LP is short for life pattern. These samples include father-son pairs that contain information at every age between 20 and 40 (son) and 30 and 50 (father). LP (Sx/Fy) classifies the LP father-son pairs around the age of x (son) and y (father). M is the share of mobile individuals, IC is the intergenerational correlation coefficient based on HISCAM, AS the controlled Altham statistic, and $\Theta_{2,x}$ the two-way log-odds ratio of category $x \in \{1, 2, 3\}$ corresponding to unskilled, skilled, and white-collar workers. The relative size of the deviation is denoted in percent of the baseline.

Table 3.10. Relative size of bias—extended Long-Ferrie classification.

Sample	M	IC	AS	$\Theta_{2,1}$	$\Theta_{2,2}$	$\Theta_{2,3}$	$\Theta_{2,4}$
Baseline	0.54	0.36	15.82	1.43	1.35	0.98	1.40
Stay	-0.56	5.97	5.47	3.46	-0.37	1.06	7.99
Ferrie (None)	-0.05	-0.04	0.27	0.75	0.08	0.72	-1.00
LP (S20/F50)	-4.07	-11.14	-6.67	8.02	22.32	9.65	-13.95
LP (S40/F40)	-2.77	-3.31	-4.11	3.33	14.91	12.58	-20.64
LP (S40/F30)	-0.55	-14.32	-5.57	0.99	13.67	7.96	-27.52

Note: Baseline marks the estimates of the mobility measures in the baseline sample. Stay denotes the sample of geographically immobile sons. Ferrie (None) is the linked sample employing Ferrie (1996) without name cleaning. LP is short for life pattern. These samples include father-son pairs that contain information at every age between 20 and 40 (son) and 30 and 50 (father). LP (Sx/Fy) classifies the LP father-son pairs around the age of x (son) and y (father). M is the share of mobile individuals, IC is the intergenerational correlation coefficient based on HISCAM, AS the controlled Altham statistic, and $\Theta_{2,x}$ the two-way log-odds ratio of category $x \in \{1, 2, 3, 4\}$ corresponding to unskilled, skilled, lower, and higher white-collar workers. The relative size of the deviation is denoted in percent of the baseline.

Appendix

3A Transition Matrices

This section contains all transition matrices referred to in the main section of this chapter.

TABLE 3A.1. TRANSITION MATRICES OF SEP—BASELINE SAMPLE.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,764	1,138	405	4,307
middle SEP (M)	1,610	2,946	753	5,309
high SEP (H)	309	731	728	1,768
Row sum	4,683	4,815	1,886	11,384

Note: The baseline sample conveys all father-son pairs available in the data.

TABLE 3A.2. TRANSITION MATRICES OF LONG-FERRIE CATEGORIES—BASELINE SAMPLE.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	5,199	1,226	681	7,106
Skilled Workers (S)	957	1,269	477	2,703
Unskilled Workers (U)	464	335	449	1,248
Row sum	6,620	2,830	1,607	11,057

Note: The baseline sample conveys all father-son pairs available in the data.

TABLE 3A.3. TRANSITION MATRICES OF EXTENDED LONG-FERRIE CATEGORIES—BASELINE SAMPLE.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1,341	793	382	182	2,698
Lower Managers (L)	1,037	2,028	844	499	4,408
Skilled Workers (S)	414	543	1,269	477	2,703
Unskilled Workers (U)	187	277	335	449	1,248
Row sum	2,979	3,641	2,830	1,607	11,057

Note: The baseline sample conveys all father-son pairs available in the data.

Table 3A.4. Transition matrices of SEP—by geographic mobility.

(a). Stayers (geographically immobile).

	Father's occupation			Column
Son's occupation	L	M	H	sum
low SEP (L)	2,030	799	250	3,079
middle SEP (M)	1,161	1,999	441	3,601
high SEP (H)	241	537	544	1,322
Row sum	3,432	3,335	1,235	8,002

(b). Return migrants.

	Father's occupation			Column
Son's occupation	L	M	H	sum
low SEP (L)	502	231	105	838
middle SEP (M)	256	564	180	1,000
high SEP (H)	44	125	119	288
Row sum	802	920	404	2,126

(C.) Emigrants.

	Father's occupation			Column
Son's occupation	L	M	H	sum
low SEP (L)	232	108	50	390
middle SEP (M)	193	383	132	708
high SEP (H)	24	69	65	158
Row sum	449	560	247	1,256

Note: The sample name refers to the emigration status of the son in the father-son pair.

Table 3A.5. Transition matrices of SEP—migrants by destination.

(a). Europe.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	237	143	68	448
middle SEP (M)	304	739	241	1,284
high SEP (H)	45	159	152	356
Row sum	586	1,041	461	2,088

(b). North America.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	107	53	25	185
middle SEP (M)	59	126	48	233
high SEP (H)	8	13	14	35
Row sum	174	192	87	453

(c). South America, Africa, Asia, or Australia.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	42	19	8	69
middle SEP (M)	63	129	27	219
high SEP (H)	4	12	11	27
Row sum	109	160	46	315

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Table 3A.6. Transition matrices of Long-Ferrie categories—by geographic mobility.

(a). Stayers (geographically immobile).

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	3,530	871	509	4,910
Skilled Workers (S)	637	898	358	1,893
Unskilled Workers (U)	325	243	366	934
Row sum	4,492	2,012	1,233	7,737

(b). Return migrants.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	998	219	101	1,318
Skilled Workers (S)	217	265	75	557
Unskilled Workers (U)	92	59	58	209
Row sum	1,307	543	234	2,084

(c). Emigrants.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	671	136	71	878
Skilled Workers (S)	103	106	44	253
Unskilled Workers (U)	47	33	25	105
Row sum	821	275	140	1,236

Note: The sample name refers to the emigration status of the son in the father-son pair.

Table 3A.7. Transition matrices of Long-Ferrie categories—migrants by destination.

(a). Europe.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	1,305	228	111	1,644
Skilled Workers (S)	130	128	41	299
Unskilled Workers (U)	53	27	27	107
Row sum	1,488	383	179	2,050

(b). North America.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	204	44	25	273
Skilled Workers (S)	54	55	23	132
Unskilled Workers (U)	24	10	10	44
Row sum	282	109	58	449

(c). South America, Africa, Asia, or Australia.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	184	40	23	247
Skilled Workers (S)	17	20	8	45
Unskilled Workers (U)	6	6	4	16
Row sum	207	66	35	308

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Table 3A.8. Transition matrices of extended Long-Ferrie categories—by geographic mobility.

(a). Stayers (geographically immobile).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	976	554	280	147	1,957
Lower Managers (L)	657	1,343	591	362	2,953
Skilled Workers (S)	257	380	898	358	1,893
Unskilled Workers (U)	126	199	243	366	934
Row sum	2,016	2,476	2,012	1,233	7,737

(b). Return migrants.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	239	156	75	22	492
Lower Managers (L)	222	381	144	79	826
Skilled Workers (S)	100	117	265	75	557
Unskilled Workers (U)	43	49	59	58	209
Row sum	604	703	543	234	2,084

(c). Emigrants.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	126	83	27	13	249
Lower Managers (L)	158	304	109	58	629
Skilled Workers (S)	57	46	106	44	253
Unskilled Workers (U)	18	29	33	25	105
Row sum	359	462	275	140	1,236

Note: The sample name refers to the emigration status of the son in the father-son pair.

Table 3A.9. Transition matrices of extended Long-Ferrie categories—migrants by destination.

(a). Europe.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	300	190	72	22	584
Lower Managers (L)	278	537	156	89	1,060
Skilled Workers (S)	67	63	128	41	299
Unskilled Workers (U)	29	24	27	27	107
Row sum	674	814	383	179	2,050

(b). North America.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	28	17	9	9	63
Lower Managers (L)	63	96	35	16	210
Skilled Workers (S)	26	28	55	23	132
Unskilled Workers (U)	11	13	10	10	44
Row sum	128	154	109	58	449

(c). South America, Africa, Asia, or Australia.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	21	16	2	0	39
Lower Managers (L)	47	100	38	23	208
Skilled Workers (S)	7	10	20	8	45
Unskilled Workers (U)	1	5	6	4	16
Row sum	76	131	66	35	308

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Table 3A.10. Transition matrices of SEP—by age at classification.

(a). Son categorized around 20, father categorized around 30.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	350	121	73	544
middle SEP (M)	151	379	125	655
high SEP (H)	48	107	122	277
Row sum	549	607	320	1,476

(b). Son categorized around 20, father categorized around 40.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	331	130	83	544
middle SEP (M)	139	383	133	655
high SEP (H)	44	108	125	277
Row sum	514	621	341	1,476

(c). Son categorized around 20, father categorized around 50.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	310	146	88	544
middle SEP (M)	129	378	148	655
high SEP (H)	44	104	129	277
Row sum	483	628	365	1,476

(d). Son categorized around 30, father categorized around 30.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	312	107	68	487
middle SEP (M)	197	411	141	749
high SEP (H)	40	89	111	240
Row sum	549	607	320	1,476

(e). Son categorized around 30, father categorized around 40.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	299	110	78	487
middle SEP (M)	179	424	146	749
high SEP (H)	36	87	117	240
Row sum	514	621	341	1,476

(F). Son categorized around 30, father categorized around 50.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	284	127	76	487
middle SEP (M)	164	418	167	749
high SEP (H)	35	83	122	240
Row sum	483	628	365	1,476

(G). Son categorized around 40, father categorized around 30.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	283	85	55	423
middle SEP (M)	221	412	151	784
high SEP (H)	45	110	114	269
Row sum	549	607	320	1,476

(H). Son categorized around 40, father categorized around 40.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	275	87	61	423
middle SEP (M)	199	429	156	784
high SEP (H)	40	105	124	269
Row sum	514	621	341	1,476

(I). Son categorized around 40, father categorized around 50.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	261	101	61	423
middle SEP (M)	181	430	173	784
high SEP (H)	41	97	131	269
Row sum	483	628	365	1,476

Note: Sons are categorized around the age of 20 (between 16 and 25), 30 (between 25 and 35), or 40 (between 35 and 45). Fathers are categorized around the age of 30, 40, and 50 +/-5.

TABLE 3A.11. TRANSITION MATRICES OF LONG-FERRIE CATEGORIES—BY AGE AT CLASSIFICATION.

(A). Son categorized around 20, father categorized around 30.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	703	158	59	920
Skilled Workers (S)	134	211	56	401
Unskilled Workers (U)	44	25	31	100
Row sum	881	394	146	1,421

(B). Son categorized around 20, father categorized around 40.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	723	146	51	920
Skilled Workers (S)	151	197	53	401
Unskilled Workers (U)	47	26	27	100
Row sum	921	369	131	1,421

(C). Son categorized around 20, father categorized around 50.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	741	132	47	920
Skilled Workers (S)	170	195	36	401
Unskilled Workers (U)	51	25	24	100
Row sum	962	352	107	1,421

(D). Son categorized around 30, father categorized around 30.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	723	182	73	978
Skilled Workers (S)	113	185	44	342
Unskilled Workers (U)	45	27	29	101
Row sum	881	394	146	1,421

(E). Son categorized around 30, father categorized around 40.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	745	171	62	978
Skilled Workers (S)	128	172	42	342
Unskilled Workers (U)	48	26	27	101
Row sum	921	369	131	1,421

(f). Son categorized around 30, father categorized around 50.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	771	154	53	978
Skilled Workers (S)	140	171	31	342
Unskilled Workers (U)	51	27	23	101
Row sum	962	352	107	1,421

(g). Son categorized around 40, father categorized around 30.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	755	208	76	1,039
Skilled Workers (S)	85	154	40	279
Unskilled Workers (U)	41	32	30	103
Row sum	881	394	146	1,421

(h). Son categorized around 40, father categorized around 40.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	785	190	64	1,039
Skilled Workers (S)	92	148	39	279
Unskilled Workers (U)	44	31	28	103
Row sum	921	369	131	1,421

(i). Son categorized around 40, father categorized around 50.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	809	174	56	1,039
Skilled Workers (S)	104	148	27	279
Unskilled Workers (U)	49	30	24	103
Row sum	962	352	107	1,421

Note: Sons are categorized around the age of 20 (between 16 and 25), 30 (between 25 and 35), or 40 (between 35 and 45). Fathers are categorized around the age of 30, 40, and 50 +/-5.

Table 3A.12. Transition matrices of extended Long-Ferrie categories—by age at classification.

(a). Son categorized around 20, father categorized around 30.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	147	104	49	20	320
Lower Managers (L)	155	297	109	39	600
Skilled Workers (S)	72	62	211	56	401
Unskilled Workers (U)	24	20	25	31	100
Row sum	398	483	394	146	1,421

(b). Son categorized around 20, father categorized around 40.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	157	102	41	20	320
Lower Managers (L)	171	293	105	31	600
Skilled Workers (S)	81	70	197	53	401
Unskilled Workers (U)	24	23	26	27	100
Row sum	433	488	369	131	1,421

(c). Son categorized around 20, father categorized around 50.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	177	89	36	18	320
Lower Managers (L)	186	289	96	29	600
Skilled Workers (S)	84	86	195	36	401
Unskilled Workers (U)	28	23	25	24	100
Row sum	475	487	352	107	1,421

(d). Son categorized around 30, father categorized around 30.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	164	115	65	24	368
Lower Managers (L)	149	295	117	49	610
Skilled Workers (S)	61	52	185	44	342
Unskilled Workers (U)	24	21	27	29	101
Row sum	398	483	394	146	1,421

(e). Son categorized around 30, father categorized around 40.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	177	110	60	21	368
Lower Managers (L)	161	297	111	41	610
Skilled Workers (S)	69	59	172	42	342
Unskilled Workers (U)	26	22	26	27	101
Row sum	433	488	369	131	1,421

(F). Son categorized around 30, father categorized around 50.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	200	96	54	18	368
Lower Managers (L)	177	298	100	35	610
Skilled Workers (S)	67	73	171	31	342
Unskilled Workers (U)	31	20	27	23	101
Row sum	475	487	352	107	1,421

(G). Son categorized around 40, father categorized around 30.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	178	129	77	26	410
Lower Managers (L)	152	296	131	50	629
Skilled Workers (S)	46	39	154	40	279
Unskilled Workers (U)	22	19	32	30	103
Row sum	398	483	394	146	1,421

(H). Son categorized around 40, father categorized around 40.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	197	124	65	24	410
Lower Managers (L)	162	302	125	40	629
Skilled Workers (S)	51	41	148	39	279
Unskilled Workers (U)	23	21	31	28	103
Row sum	433	488	369	131	1,421

(I). Son categorized around 40, father categorized around 50.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	220	110	61	19	410
Lower Managers (L)	178	301	113	37	629
Skilled Workers (S)	51	53	148	27	279
Unskilled Workers (U)	26	23	30	24	103
Row sum	475	487	352	107	1,421

Note: Sons are categorized around the age of 20 (between 16 and 25), 30 (between 25 and 35), or 40 (between 35 and 45). Fathers are categorized around the age of 30, 40, and 50 +/-5.

Table 3A.14. Transition matrices of SEP—by name cleaning procedure (Ferrie).

(a). Ferrie (NYSIIS).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,312	974	283	3,569
middle SEP (M)	1,422	2,541	591	4,554
high SEP (H)	245	575	549	1,369
Row sum	3,979	4,090	1,423	9,492

(b). Ferrie (Soundex).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,307	971	282	3,560
middle SEP (M)	1,416	2,538	591	4,545
high SEP (H)	245	574	549	1,368
Row sum	3,968	4,083	1,422	9,473

(c). Ferrie (None).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,312	974	283	3,569
middle SEP (M)	1,422	2,541	591	4,554
high SEP (H)	245	575	549	1,369
Row sum	3,979	4,090	1,423	9,492

Note: The sample name refers to the linking procedure employed to match fathers and sons.

Table 3A.15. Transition matrices of SEP—by name cleaning procedure (Abramitzky).

(a). Abramitzky (NYSIIS).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,196	916	266	3,378
middle SEP (M)	1,360	2,414	548	4,322
high SEP (H)	218	546	486	1,250
Row sum	3,774	3,876	1,300	8,950

(b). Abramitzky (Soundex).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,638	1,080	376	4,094
middle SEP (M)	1,540	2,813	706	5,059
high SEP (H)	293	687	673	1,653
Row sum	4,471	4,580	1,755	10,806

(c). Abramitzky (None).

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2,202	920	267	3,389
middle SEP (M)	1,364	2,422	552	4,338
high SEP (H)	218	547	487	1,252
Row sum	3,784	3,889	1,306	8,979

Note: The sample name refers to the linking procedure employed to match fathers and sons.

Table 3A.16. Transition matrices of Long-Ferrie categories—by name cleaning procedure (Ferrie).

(a). Ferrie (NYSIIS).

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	4,299	1,074	576	5,949
Skilled Workers (S)	761	1,039	393	2,193
Unskilled Workers (U)	376	280	390	1,046
Row sum	5,436	2,393	1,359	9,188

(b). Ferrie (Soundex).

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	4,297	1,071	573	5,941
Skilled Workers (S)	758	1,034	393	2,185
Unskilled Workers (U)	376	278	390	1,044
Row sum	5,431	2,383	1,356	9,170

(c). Ferrie (None).

	Father's occupation			Column
Son's occupation	W	S	U	sum
White-Collar (W)	4,299	1,074	576	5,949
Skilled Workers (S)	761	1,039	393	2,193
Unskilled Workers (U)	376	280	390	1,046
Row sum	5,436	2,393	1,359	9,188

Note: The sample name refers to the linking procedure employed to match fathers and sons.

Table 3A.17. Transition matrices of Long-Ferrie categories—by name cleaning procedure (Abramitzky).

(a). Abramitzky (NYSIIS).

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	4,042	1,008	548	5,598
Skilled Workers (S)	714	979	377	2,070
Unskilled Workers (U)	349	271	364	984
Row sum	5,105	2,258	1,289	8,652

(b). Abramitzky (Soundex).

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	4,923	1,173	646	6,742
Skilled Workers (S)	893	1,199	453	2,545
Unskilled Workers (U)	445	317	434	1,196
Row sum	6,261	2,689	1,533	10,483

(c). Abramitzky (None).

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	4,056	1,012	549	5,617
Skilled Workers (S)	717	981	377	2,075
Unskilled Workers (U)	350	273	365	988
Row sum	5,123	2,266	1,291	8,680

Note: The sample name refers to the linking procedure employed to match fathers and sons.

Table 3A.18. Transition matrices of extended Long-Ferrie categories—by name cleaning procedure (Ferrie).

(a). Ferrie (NYSIIS).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1,025	662	328	144	2,159
Lower Managers (L)	844	1,768	746	432	3,790
Skilled Workers (S)	296	465	1,039	393	2,193
Unskilled Workers (U)	134	242	280	390	1,046
Row sum	2,299	3,137	2,393	1,359	9,188

(b). Ferrie (Soundex).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1,025	661	328	142	2,156
Lower Managers (L)	844	1,767	743	431	3,785
Skilled Workers (S)	294	464	1,034	393	2,185
Unskilled Workers (U)	134	242	278	390	1,044
Row sum	2,297	3,134	2,383	1,356	9,170

(c). Ferrie (None).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1,025	662	328	144	2,159
Lower Managers (L)	844	1,768	746	432	3,790
Skilled Workers (S)	296	465	1,039	393	2,193
Unskilled Workers (U)	134	242	280	390	1,046
Row sum	2,299	3,137	2,393	1,359	9,188

Note: The sample name refers to the linking procedure employed to match fathers and sons.

Table 3A.19. Transition matrices of extended Long-Ferrie categories—by name cleaning procedure (Abramitzky).

(a). Abramitzky (NYSIIS).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	956	622	297	136	2,011
Lower Managers (L)	783	1,681	711	412	3,587
Skilled Workers (S)	269	445	979	377	2,070
Unskilled Workers (U)	125	224	271	364	984
Row sum	2,133	2,972	2,258	1,289	8,652

(b). Abramitzky (Soundex).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1,243	758	369	175	2,545
Lower Managers (L)	972	1,950	804	471	4,197
Skilled Workers (S)	385	508	1,199	453	2,545
Unskilled Workers (U)	173	272	317	434	1,196
Row sum	2,773	3,488	2,689	1,533	10,483

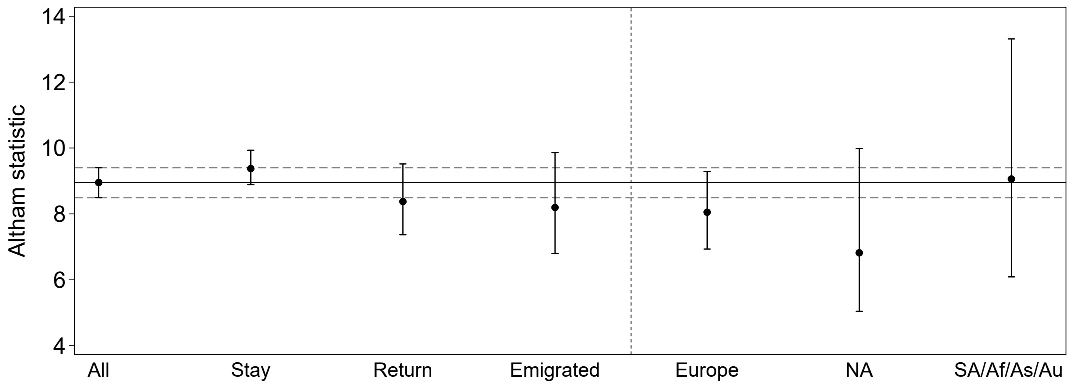
(c). Abramitzky (None).

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	959	623	298	136	2,016
Lower Managers (L)	787	1,687	714	413	3,601
Skilled Workers (S)	271	446	981	377	2,075
Unskilled Workers (U)	125	225	273	365	988
Row sum	2,142	2,981	2,266	1,291	8,680

Note: The sample name refers to the linking procedure employed to match fathers and sons.

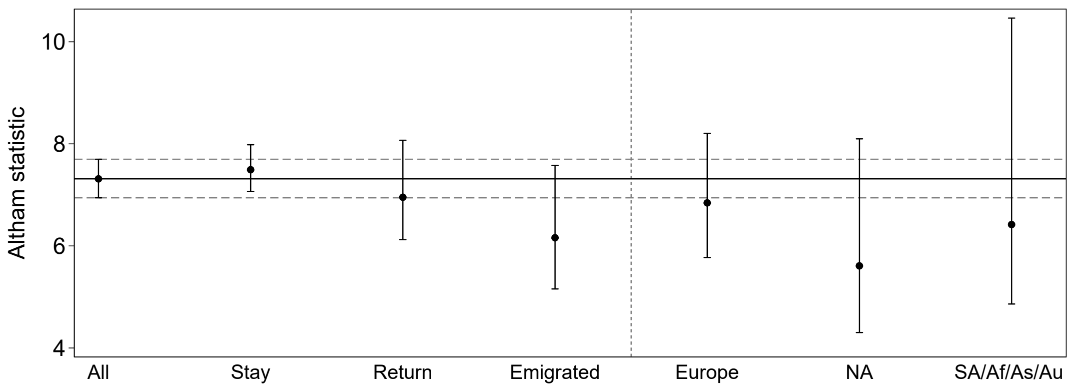
3B Supplementary Figures and Tables

Figure 3B.1. Raw Altham statistic according to SEP categories by migration status.



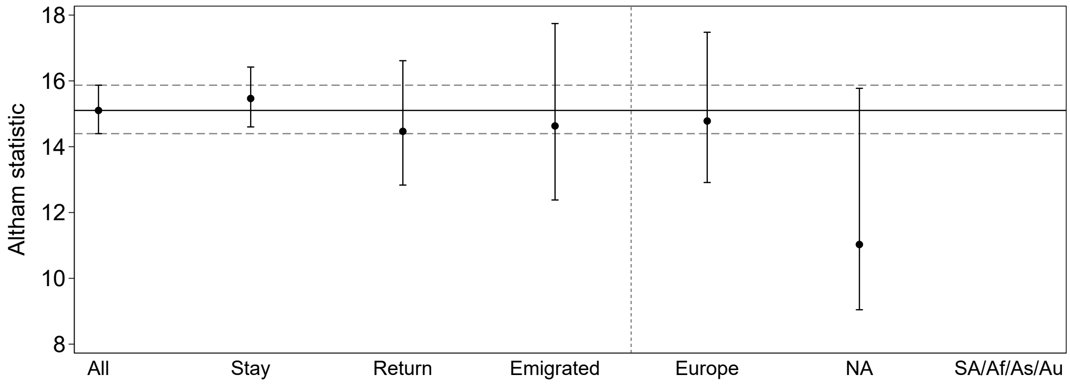
Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3B.2. Raw Altham statistic according to Long-Ferrie categories by migration status.



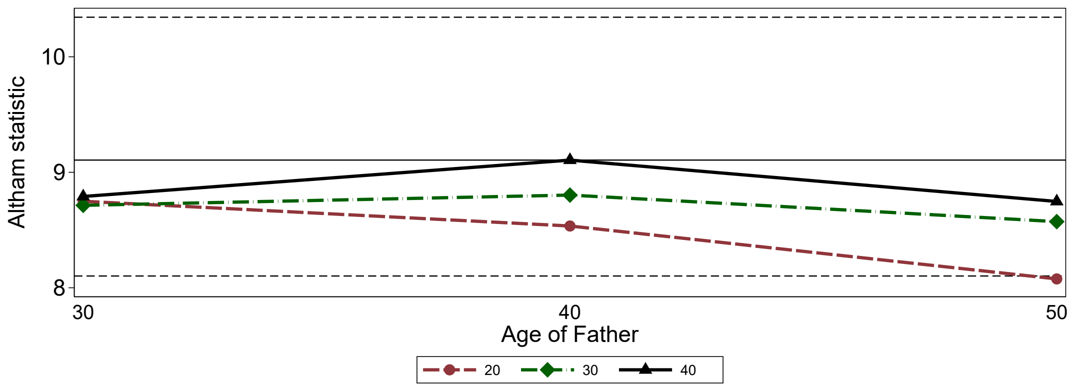
Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3B.3. Raw Altham statistic according to extended Long-Ferrie categories by migration status.



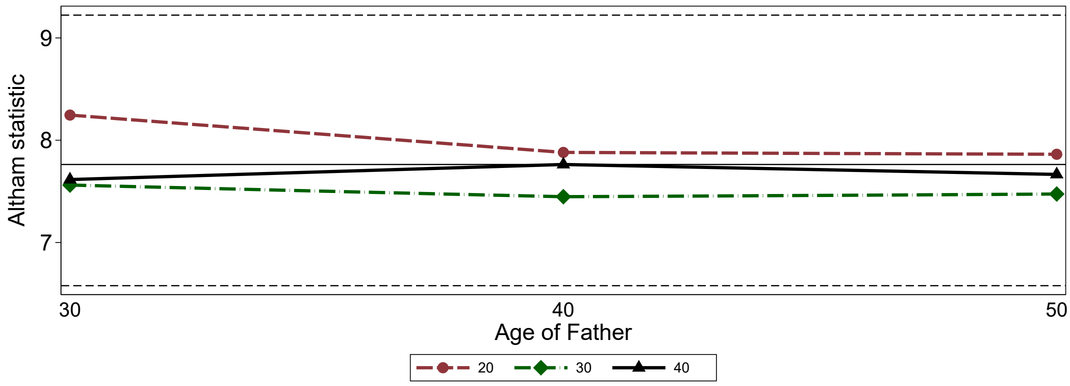
Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (All). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8). The groups to the RHS of the vertical dashed line are geographically mobile (Return and Emigrated) split by destination.

Figure 3B.4. Raw Altham statistic according to SEP categories by age at classification.



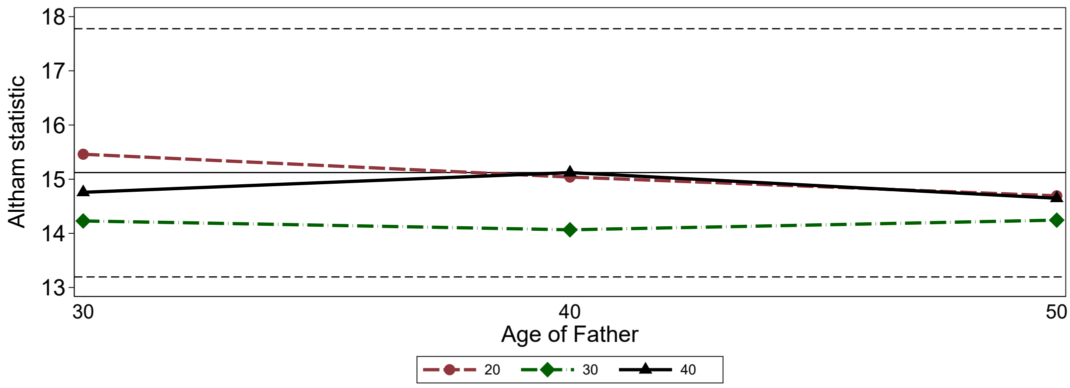
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3B.5. Raw Altham statistic according to Long-Ferrie categories by age at classification.



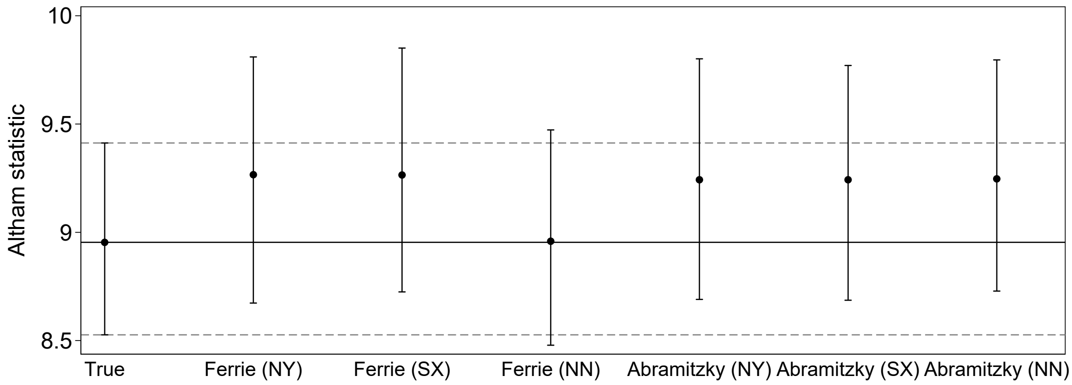
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3B.6. Raw Altham statistic according to extended Long-Ferrie categories by age at classification.



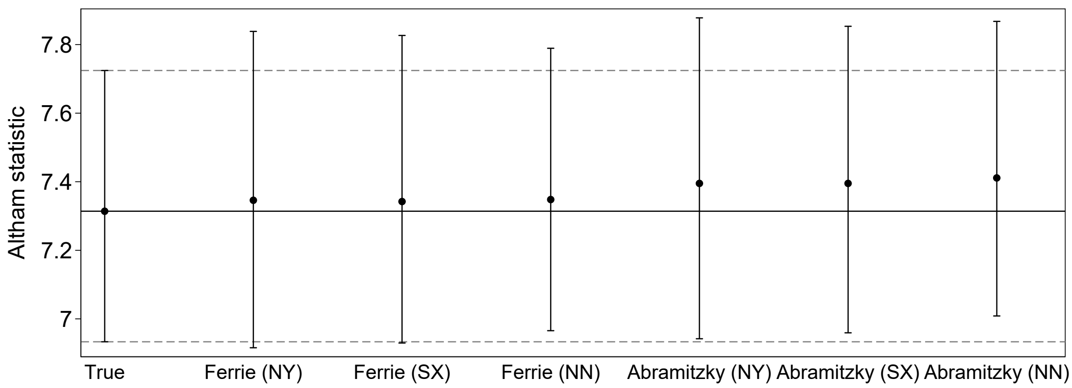
Note: The age at classification of the son is color-coded (see legend); the father's age at classification is on the x-axis. This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) of the 40-40 sample (both son and father categorized at age 40). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3B.7. Raw Altham statistic according to SEP categories by linking procedure.



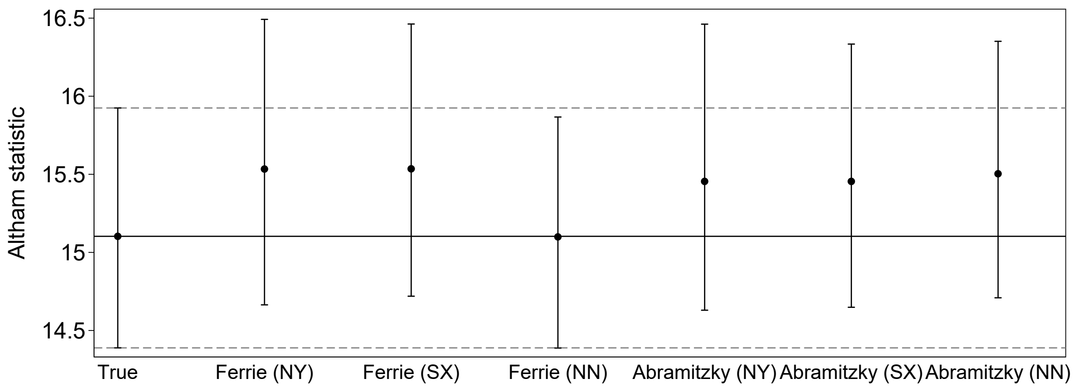
Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3B.8. Raw Altham statistic according to Long-Ferrie categories by linking procedure.



Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Figure 3B.9. Raw Altham statistic according to extended Long-Ferrie categories by linking procedure.



Note: This figure contains the uncontrolled Altham statistic. The horizontal lines mark the level (solid) and confidence intervals (dashed) for the baseline sample (True). Confidence intervals are calculated by a bootstrapping procedure as explained in Modalsli (2015, p. 8).

Table 3B.1. Descriptive statistics of father-son pairs with sons migrating to South America, Africa, Asia, and Australia.

Characteristic	SA	Australia	Asia	Africa
Number of observations	146	50	106	21
Age	35.68	34.27	35.40	34.22
Age at Migration	26.59	26.09	25.25	24.64
Low SEP [pct]	31.33	19.23	10.28	13.04
Middle SEP [pct]	62.00	69.23	80.37	69.57
High SEP [pct]	6.67	11.54	9.35	17.39
Unskilled workers [pct]	5.41	9.80	1.92	4.35
Skilled workers [pct]	21.62	7.84	7.69	8.70
White-collar [pct]	72.97	82.35	90.38	86.96
Lower managers [pct]	62.84	64.71	76.92	73.91
Higher managers [pct]	10.14	17.65	13.46	13.04
Age (f)	44.35	45.29	43.87	49.26
Low SEP [pct] (f)	35.67	26.92	34.78	33.33
Middle SEP [pct] (f)	49.68	50.00	47.83	52.38
High SEP [pct] (f)	14.65	23.08	17.39	14.29
Unskilled workers [pct] (f)	11.46	9.62	13.16	9.52
Skilled workers [pct] (f)	24.84	15.38	20.18	14.29
White-collar [pct] (f)	63.69	75.00	66.67	76.19
Lower managers [pct] (f)	39.49	46.15	38.60	42.86
Higher managers [pct] (f)	24.20	28.85	28.07	33.33

Note: The number of observations refers to the number of father-son pairs by destination continent. Note that one father-son pair may be included in more than one sub-sample because of multiple migration. Age is the age at observed occupation closest to forty. Age at Migration denotes the sons' age at first migration. The remainder of the table describes the distribution across occupational classes in percent. Lower managers and higher managers are encompassed in the white-collar group. Rows with an (f) capture the values for the fathers, those without an (f) capture the values for the sons.

Table 3B.2. Transition matrices of SEP—migrants to South America, Africa, Asia, and Australia.

(a). South America.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	28	13	4	45
middle SEP (M)	22	60	10	92
high SEP (H)	3	2	4	9
Row sum	53	75	18	146

(b). Africa.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	2	1	0	3
middle SEP (M)	5	8	2	15
high SEP (H)	0	2	1	3
Row sum	7	11	3	21

(c). Asia.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	6	2	3	11
middle SEP (M)	30	46	9	85
high SEP (H)	1	5	4	10
Row sum	37	53	16	106

(d). Australia.

Son's occupation	Father's occupation L	M	H	Column sum
low SEP (L)	6	3	1	10
middle SEP (M)	8	19	7	34
high SEP (H)	0	3	3	6
Row sum	14	25	11	50

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Table 3B.3. Transition matrices of Long-Ferrie categories—migrants to South America, Africa, Asia, and Australia.

(a). South America.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	78	18	9	105
Skilled Workers (S)	10	15	6	31
Unskilled Workers (U)	3	4	1	8
Row sum	91	37	16	144

(b). Africa.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	15	1	2	18
Skilled Workers (S)	1	1	0	2
Unskilled Workers (U)	0	1	0	1
Row sum	16	3	2	21

(c). Asia.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	64	18	10	92
Skilled Workers (S)	4	3	1	8
Unskilled Workers (U)	1	0	1	2
Row sum	69	21	12	102

(d). Australia.

Son's occupation	Father's occupation W	S	U	Column sum
White-Collar (W)	33	5	2	40
Skilled Workers (S)	2	1	1	4
Unskilled Workers (U)	2	1	2	5
Row sum	37	7	5	49

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Table 3B.4. Transition matrices of extended Long-Ferrie categories—migrants to South America, Africa, Asia, and Australia.

(a). South America.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	7	6	1	0	14
Lower Managers (L)	20	45	17	9	91
Skilled Workers (S)	4	6	15	6	31
Unskilled Workers (U)	1	2	4	1	8
Row sum	32	59	37	16	144

(b). Africa.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	1	2	0	0	3
Lower Managers (L)	6	6	1	2	15
Skilled Workers (S)	0	1	1	0	2
Unskilled Workers (U)	0	0	1	0	1
Row sum	7	9	3	2	21

(c). Asia.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	9	4	1	0	14
Lower Managers (L)	16	35	17	10	78
Skilled Workers (S)	2	2	3	1	8
Unskilled Workers (U)	0	1	0	1	2
Row sum	27	42	21	12	102

(d). Australia.

Son's occupation	Father's occupation H	L	S	U	Column sum
Higher Managers (H)	5	4	0	0	9
Lower Managers (L)	8	16	5	2	31
Skilled Workers (S)	1	1	1	1	4
Unskilled Workers (U)	0	2	1	2	5
Row sum	14	23	7	5	49

Note: These tables only contain father-son pairs with geographically mobile sons. The sample name refers to the destination continent(s).

Chapter 4

Offsetting the Cliff?
A Sufficient Statistics Approach to Measuring the Welfare Effects of Work Incentives in Disability Insurance

Joint with Andreas Haller and Stefan Staubli

Abstract: In most disability insurance (DI) programs, DI recipients lose their entire cash benefits if they have labor earnings beyond a certain income threshold. Introducing a benefit offset program reduces DI cash benefits gradually beyond this threshold. This has two opposing effects: (1) the most able DI beneficiaries are incentivized to increase their labor supply (labor supply effect), reducing program costs, and (2) DI becomes more attractive for potential applicants, which might cause more DI take-up (induced entry effect), increasing program costs. This paper develops robust sufficient statistics formulas to evaluate the welfare effects of such a reform. We show that the welfare effects crucially depend on two sufficient statistics: (1) the earnings elasticity of DI recipients (capturing the labor supply effect), and (2) the DI benefit take-up elasticity (capturing the induced entry effect). In an empirical application of our model, we plan to estimate these two sufficient statistics using policy reforms in Canada. Using existing estimates from previous studies on the United States, we find that it is unlikely that the introduction of a benefit offset reduces program expenditures. However, it can still be welfare improving for reasonable values of risk aversion.

JEL classification: J14, H21, I30, D14.
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4.1 Introduction

In many countries, the share of individuals receiving disability insurance (DI) has increased significantly over the past few decades. Autor et al. (2018) line out that, in the United States, the number of DI recipients has quintupled to over 5 percent and that European countries such as Norway exhibit an even stronger increase over the past five decades. The rapid expansion of the beneficiary population has generated substantial interest by policy makers and economists in measures that reduce growth in program caseloads and expenditures. Autor and Duggan (2006) discuss three ways to limit the expansion of DI programs: (1) provide incentives to return to work, (2) reduce incentives to seek DI benefits, and (3) adopt more rigorous eligibility standards. This paper focuses on the first approach, the optimal financial work incentives in DI.

DI programs are known for their strong work disincentives (Autor and Duggan, 2003; Bound et al., 2010). Most DI programs feature so-called "cash cliffs": If DI beneficiaries supply work above a certain income threshold (the earnings disregard), they lose their entire cash benefits. Instead, a benefit offset program reduces DI cash benefits gradually for individuals with an income above the earnings disregard. Figure 4.1 (on p. 170) illustrates a stylized budget set of DI beneficiaries under a cash cliff and a benefit offset regime. Intuitively, the introduction of a benefit offset scheme has two opposing effects. On the one hand, it can mitigate the inclusion error in DI. The most able DI beneficiaries are incentivized to increase their labor supply (labor supply effect). This reduces program costs without reducing the insurance value of DI. Empirical evidence on substantial remaining work capacity of some DI recipients[1] underlines the potential importance of this effect. On the other hand, the introduction of a benefit offset scheme makes DI more attractive for potential applicants. This might cause more DI take-up (induced entry effect), which increases program costs.

This paper formalizes the trade-off between labor supply and induced entry effect in a sufficient statistics model. For welfare analyses, we develop robust sufficient statistics formulas that capture the insurance value and incentive costs of benefit offset schemes. These formulas are functions of high-level elasticities that can be estimated using design-based empirical methods. We show that the welfare effects of moving from a cash cliff to a benefit offset regime crucially depend on two sufficient statistics: (1) the earnings

[1] See for instance Maestas et al. (2013) and Autor et al. (2015).

elasticity of DI recipients, and (2) the DI benefit take-up elasticity.[2] The earnings elasticity captures the labor supply effect. The DI benefit take-up elasticity is a sufficient statistic for induced entry in a broad class of models. The contribution of our theoretical analysis is twofold. First, it provides simple yet robust sufficient statistics formulas to evaluate the welfare effects of introducing a benefit offset. Second, it sheds light on the potential size of the induced entry effect based on credible reduced form estimates. Estimating the induced entry effect is a key challenge. While the labor supply effect of a \$ 1 for \$ 2 benefit offset has been tested recently in the large benefit offset national demonstration (BOND) field experiment, the induced entry effect cannot be studied in a randomized controlled trial. The size of the induced entry is usually estimated by structural models (e.g. Hoynes and Moffitt, 1999 or Benitez-Silva et al., 2010). Our approach shows that in a broad class of models the DI benefit take-up elasticity is informative on the size of the induced entry effect.

We currently work on estimating both the benefit take-up elasticity and the earnings elasticity for Canada with data from the Longitudinal Administrative Database (LAD). Canada operates distinct DI programs for Quebec and the Rest of Canada (RoC). We exploit two policy reforms that provide exogenous variation in the DI benefit level and the earnings disregard in RoC but not in Quebec. This allows us to estimate the causal effects of the two reforms employing a difference-in-differences (DiD) identification strategy. Further, the earnings disregard allows us to estimate the earnings elasticity with a bunching estimator. This is work in progress. For the time being, we use estimates from previous studies to evaluate the welfare effects of introducing a benefit offset scheme. For the United States, we find that it is unlikely that the introduction of a benefit offset scheme reduces program expenditures. However, replacing the cash cliff with an offset can be welfare improving for reasonable values of risk aversion depending on the benefit take-up elasticity. The estimates for the benefit take-up elasticity in the literature range from 0.1 to 0.9. For the smallest value, our sufficient statistic formula suggests that the introduction of a benefit offset is welfare improving. For the largest reported elasticity, it is better to keep the cash cliff, which acts as guard against undesirable DI applications. We hope to provide credible estimates of the benefit take-up elasticity with our empirical approach employing Canadian data.

[2]The DI benefit take-up elasticity denotes the elasticity of DI claiming with respect to benefit generosity, i.e. by how many percent DI claiming increases if DI benefits increase by 1 percent.

There is a growing empirical literature studying the effects of DI on labor market outcomes (e.g. Autor and Duggan, 2003; de Jong et al., 2011; Staubli, 2011; Maestas et al., 2013; French and Song, 2014; Moore, 2015; Gelber et al., 2017; Deshpande et al., 2019) but empirical evidence on benefit offset schemes is scarce. A few countries tested the effects of benefit offset schemes on the labor supply of DI beneficiaries. In the United States, the Social Security Administration recently ran a field experiment to test a benefit offset policy that reduces benefits by $ 1 for every $ 2 of earnings above the earnings disregard (in the United States: substantial gainful activity (SGA)). Gubits et al. (2018) provide the final evaluation of this field experiment. They report that the probability of employment increased by 2 percent (0.4 percentage points) in the entire DI population and by 4 percent (2 percentage points) in a volunteer population, which is thought most likely to use the offset.[3] Moreover, they document a 7 percent (0.4 percentage points) increase in the share of individuals whose earnings exceed the SGA in the DI population and a corresponding increase of 25 percent (4 percentage points) in the volunteer population. They conclude that the small estimated increases in earnings (not statistically significant) were not sufficient to offset the deadweight loss from increases in taxes needed to fund larger DI benefit payments.[4] Switzerland also conducted a field experiment on the introduction of a conditional cash program that incentivizes work but exhibited a low take-up rate of 0.5 percent (Bütler et al., 2015). Campolieti and Riddell (2012) evaluate a shift in the earnings disregard in Canada. They report an increase in the extensive labor supply margin but no effect on program entry or exit. Kostol and Mogstad (2014) estimate the labor supply effects of a benefit offset scheme in Norway. In 2005, Norway introduced a benefit offset program that allowed DI beneficiaries to keep NOK 0.40 of every NOK 1.00 earned above an earning threshold. Because only DI beneficiaries who were already on DI before January 1 of 2004 became eligible for this benefit offset, they can use a regression discontinuity design to estimate the labor supply effects. They find substantial positive impacts on labor supply. Three years after implementation, this benefit offset increased labor force participation by 8.5 percentage points for DI recipients under age 50. Ruh and Staubli (forthcoming) exploit bunching at the earnings disregard to identify the earnings elasticity of DI recipients in Austria and report an elasticity of 0.27. Gelber et al. (2017)

[3]Gubits et al. (2018) explain the two treatment groups in greater detail.

[4]DI benefit payments increased by roughly 1 percent ($ 12 per month) in the entire DI population and by roughly 4 percent ($ 37 per month) in the volunteer population.

study how differences in benefit levels reduce labor supply through an income effect of DI recipients in the United States documenting that this income effect accounts for a majority of DI-induced reductions in earnings. However, these studies and experiments can only identify the labor supply effect of individuals already on DI. The induced entry effect of benefit offset schemes is difficult to estimate with reduced form methods. Therefore, structural models have been used to estimate the induced entry effect. Hoynes and Moffitt (1999) simulate the potential effects of a benefit offset for the United States in a calibrated model. More recently, Benitez-Silva et al. (2010) simulate the effect of the United States \$ 1 for \$ 2 offset in a structural model.

To our knowledge, there is very little theoretical research on work incentives in DI. Parsons (1996) shows that in a model with two-sided classification errors and two ability types, it is desirable to provide work incentives if there are no application fees. With application fees, a system without work incentives can be more efficient. Inderbitzin and Wallimann (2013) study the optimal work incentives with a distribution of ability types and an extensive margin labor supply choice. They find that the efficiency of work incentives depends on the relative size of labor supply and induced entry effects. In this sense, we generalize their model to include the intensive margin, which is the main target of work incentives in DI, and derive implementable sufficient statistics formulas.

The remainder of this paper is structured as follows. Section 4.2 describes our theoretical model. Section 4.3 discusses the welfare implications of our model employing existing estimates from the literature. Section 4.4 previews our empirical approach to estimating the labor supply and the benefit take-up elasticity for Canada. Section 4.5 concludes.

4.2 Model

In this section, we present a simple model of disability insurance (DI) based on the seminal work of Diamond and Sheshinski (1995). This model allows us to derive optimality conditions in terms of behavioral parameters that serve as sufficient statistics to evaluate the (local) optimality of work incentives in DI. Importantly, these behavioral parameters can be estimated empirically. We employ this model to study two questions: (1) Given a benefit offset scheme, what is the optimal offset rate r, i.e. what share of income above the earnings disregard should DI beneficiaries be allowed to keep? And (2) what are the fiscal and the welfare effects of replacing a cash cliff regime with a benefit offset scheme?

One key finding is that the answers to these two questions are closely related. We show that a cash cliff system can be modeled as a specific form of a benefit offset regime. Hence, shifting from a cash cliff to a benefit offset program is a special case of adjusting the offset rate under a benefit offset system. In Section 4.2.1, we describe the model setup. Section 4.2.2 discusses the optimal offset rate, and Section 4.2.3 discusses the welfare effects of replacing a cash cliff with a benefit offset. In Section 4.2.4, we discuss various extensions.

4.2.1 Setup

We expand the seminal DI model of Diamond and Sheshinski (1995) by introducing an intensive labor supply choice and a two period structure. In the first period, the agent works, earns a wage w, and pays lump-sum taxes τ to finance the DI program. She does not save, does not make any other choices in the first period, and yields utility $u(w-\tau)$. In the second period, the agent suffers a disability shock θ, drawn from a continuous distribution $F(\theta)$.[5] After the agent observes the disability shock, she can choose whether to apply to DI and how much to work in either case.[6]

Labor Supply Decision Individuals with disability type θ choose their labor supply $z(\theta) \geq 0$ by maximizing

$$z(\theta) := \underset{z \geq 0}{\operatorname{argmax}}\, u(c(z)) - h(z,\theta), \tag{4.1}$$

where $h(z,\theta)$ denotes the disutility of labor of type θ when earning z, and $c(z)$ denotes disposable income. The wage rate is normalized to one for simplicity. We assume that $u_z > 0$, $u_{zz} < 0$, $h_z > 0$, $h_{zz} > 0$, $h_\theta > 0$, $h_{z\theta} > 0$, and $u(0) = h(0,\theta) = 0$ such that u is concave and h is convex. This implies a unique optimal labor supply, $z(\theta)$, for every θ, declining optimal labor supply in θ ($z'(\theta) \leq 0$), and convex indifference curves in consumption and labor income.[7]

[5] We consider $\theta \in [0,\infty)$ as disability or "disutility of work". Thus, a higher θ corresponds to a more severe disability and higher disutility of work.

[6] For ease of exposition, we present the simplest possible model in the main text. In Section 4.2.4 and the Appendix, we discuss various extensions and show that our results hold in a broad class of models.

[7] Moreover, individuals with higher θ have steeper indifference curves, guaranteeing single crossing of indifference curves. Our theoretical insights do not rely on the specification with separable utility. Our insights apply for all specifications with convex preferences and single crossing of indifference curves for different θ-types. We present this specification for notational simplicity.

Disposable Income For simplicity, we assume there are no taxes in the second period for non-DI recipients. Thus, their disposable labor income is given by $c(z) = z$. DI recipients face labor income taxes. We consider two tax regimes: a cash cliff and a benefit offset regime.

A benefit offset scheme consists of three parameters (b, r, SGA). b denotes the base DI benefits, i.e. the benefits an individual receives if she works less than the threshold SGA. r is the marginal tax rate of labor income above SGA. Hence, r is the rate at which benefits are reduced for every dollar earned beyond SGA. An individual who earns labor income $z^B(\theta)$ has disposable income

$$c^B(\theta) = \begin{cases} b + z^B(\theta), & \text{if } z^B(\theta) \leq SGA, \\ b + SGA + (1-r)(z^B(\theta) - SGA), & \text{if } z^B(\theta) > SGA, \end{cases} \tag{4.2}$$

under a benefit offset scheme. With $r = 1$, benefits would be reduced one by one for labor income above SGA. With $r = 0$ benefits are independent of earnings. A lower r, therefore, corresponds to higher work incentives and a lower benefit offset.

DI with a cash cliff is characterized by two parameters (b, SGA), where b is the DI benefits an individual receives as long as she earns a labor income below the earnings disregard SGA. If she earns above SGA she loses all her benefits. Hence, under a cash cliff an individual with optimal labor supply $z^C(\theta)$ has disposable income

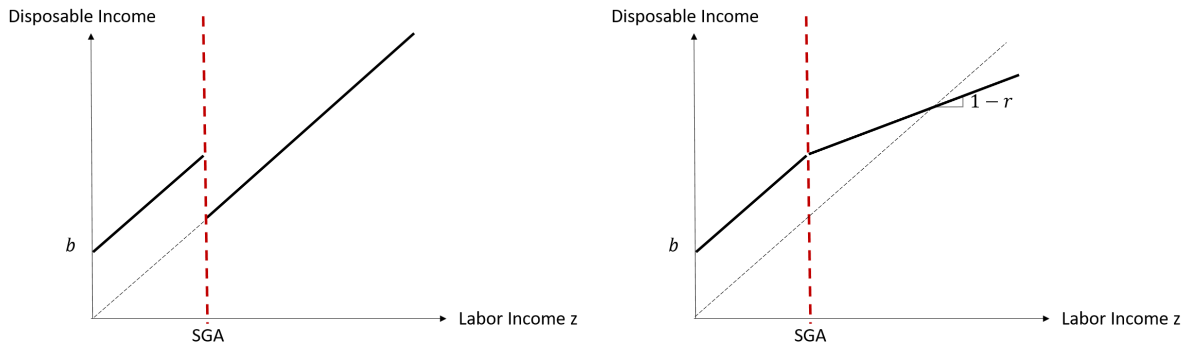
$$c^C(\theta) = \begin{cases} b + z^C(\theta), & \text{if } z^C(\theta) \leq SGA, \\ z^C(\theta), & \text{if } z^C(\theta) > SGA. \end{cases} \tag{4.3}$$

Figure 4.1 illustrates the budget set of individuals under the cash cliff vs the benefit offset scheme. The black dotted line represents the budget set of non-DI recipients.

DI Application Decision There exists a unique marginal DI applicant θ^A. Individuals with a lower disability level than the marginal applicant ($\theta < \theta^A$) do not apply for DI benefits, work according to their optimal labor supply choice $z(\theta)$, and receive utility $u(z(\theta)) - h(z(\theta), \theta)$. Individuals with a higher degree of disability than the marginal applicant ($\theta \geq \theta^A$) apply for DI benefits. As in Diamond and Sheshinski (1995), a DI application is accepted with probability $p(\theta)$, where p increases in θ. An accepted

Figure 4.1. Budget sets under cash cliff vs benefit offset scheme.

(a). Cash cliff. (b). Benefit offset.



Note: b denotes the base DI benefits, SGA the earnings disregard, and r the offset rate.

applicant chooses her optimal labor supply $z^i(\theta)$, yielding second-period utility $u(c^i(\theta)) - h(z^i(\theta), \theta)$ where $i \in \{B, C\}$, depending on whether there is a benefit offset (B) or cash cliff (C) regime in place. A rejected applicant goes back to work and gets second-period utility $u(z(\theta)) - h(z(\theta), \theta)$.

4.2.2 Optimal Benefit Offset

Under a benefit offset regime with parameters (b, r, SGA), social welfare is given by

$$\begin{aligned} W =& u(w-\tau) + \int_0^{\theta^A} u(z(\theta)) - h(z(\theta), \theta) dF(\theta) + \int_{\theta^A}^{\infty} p(\theta)[u(c^B(\theta)) - h(z^B(\theta), \theta)] dF(\theta) \\ &+ \int_{\theta^A}^{\infty} [1 - p(\theta)][u(z(\theta)) - h(z(\theta), \theta)] dF(\theta). \end{aligned} \tag{4.4}$$

The government budget constraint corresponds to

$$\begin{aligned} \tau &= \int_{\theta^A}^{\infty} p(\theta) \left(\mathbb{1}\{z^B(\theta) \le SGA\} b + \mathbb{1}\{z^B(\theta) > SGA\} \left[b - r(z^B(\theta) - SGA) \right] \right) dF(\theta) \\ &= \int_{\theta^A}^{\infty} p(\theta)(b - ry(\theta)) dF(\theta), \end{aligned} \tag{4.5}$$

where y is defined as income above the earnings disregard, i.e.

$$y(\theta) = \begin{cases} z^B(\theta) - SGA, & \text{if } z^B(\theta) \ge SGA \\ 0, & \text{if } z^B(\theta) < SGA. \end{cases} \tag{4.6}$$

The marginal applicant θ^A is unique and determined by[8]

$$u(b + SGA + (1-r)(z^B(\theta^A) - SGA)) - h(z^B(\theta^A), \theta^A) = u(z(\theta^A)) - h(z(\theta^A), \theta^A), \quad (4.7)$$

where $z^B(\theta^A)$ solves

$$(1-r)u'(b + SGA + (1-r)(z^B(\theta^A) - SGA)) = h_z(z^B(\theta^A), \theta^A), \quad (4.8)$$

and $z(\theta^A)$ solves

$$u'(z(\theta^A)) = h_z(z(\theta^A), \theta^A). \quad (4.9)$$

Moreover, we have $SGA \leq z^B(\theta^A) < z_K$, where z_K is the intersection of the benefit offset and the regular budget set, and $z^B(\theta^A) < z(\theta^A)$.[9]

A marginal change in the offset rate r has a welfare effect of

$$\frac{\partial W}{\partial r} = -u'(w-\tau)\frac{\partial \tau}{\partial r} - \underbrace{\int_{\theta^A}^{\infty} p(\theta)u'(c^B(\theta))y(\theta)dF(\theta)}_{\text{change in insurance value}}, \quad (4.10)$$

where

$$\frac{\partial \tau}{\partial r} = \underbrace{-\frac{\partial \theta^A}{\partial r} f(\theta^A)p(\theta^A)}_{\text{induced entry effect}} \left[b - ry(\theta^A)\right] - r\int_{\theta^A}^{\infty} p(\theta) \underbrace{\frac{\partial y(\theta)}{\partial r}}_{\text{labor supply effect}} dF(\theta) \quad (4.11)$$
$$- \underbrace{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}_{\text{mechanical costs}}.$$

Intuitively, lowering the offset rate r increases the insurance value for DI recipients, who earn above SGA, i.e. have $y(\theta) > 0$. All behavioral responses, such as more labor supply and more applications, do not have first order welfare effects because of the envelope theorem. The behavioral responses only enter through the fiscal effects $\partial\tau/\partial r$. The fiscal effects consist of three components. First, a lower benefit offset increases expendi-

[8] Note that this is an interior solution in the sense that the marginal applicant supplies more labor than SGA. In case the marginal applicant would actually want to work less than or at SGA, the benefit offset would not be effective. Hence, the scenario would correspond to the one discussed in Section 4.2.3. Thus, we only consider benefit offset schemes with interior solutions, i.e. $1 - r \geq \frac{h_z(SGA,\theta^A)}{u'(b+SGA)}$, throughout this section.

[9] For proof, see Lemma 2 in the Appendix.

tures mechanically through lower taxes on labor incomes above the earnings disregard. Second, the labor supply incentives change, which causes a behavioral response of DI recipients' labor supply. Third, DI becomes more attractive for individuals with disability levels just below the previous marginal applicant, which leads to more entry into DI.

From equation (4.10), it follows immediately that providing more work incentives, i.e. reducing r, is always welfare improving if this reduces program expenditures, i.e. $\partial\tau/\partial r > 0$. In this case, decreasing the benefit offset, r, is a Pareto improvement. However, $\partial\tau/\partial r > 0$ is rather unlikely to hold. Even in the absence of induced entry, i.e. $-\frac{\partial\theta^A}{\partial r} f(\theta^A)p(\theta^A)\left[b - ry(\theta^A)\right] = 0$, the labor supply effect would have to compensate the mechanical costs in order to reduce program expenditures. If there is induced entry, the labor supply effect needs to be even stronger. This means, we would, at least, need that

$$1 < -\int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta)\frac{r}{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)} =: \varepsilon, \tag{4.12}$$

where ε is the earnings elasticity of DI recipients who earn above the earnings disregard. Hence, for an expenditure reduction, we need, at least, an earnings elasticity above one. If there is a positive induced entry effect on top, i.e. $-\frac{\partial\theta^A}{\partial r} f(\theta^A)p(\theta^A)\left[b - ry(\theta^A)\right] < 0$, the earnings elasticity needs to be even larger. Earnings elasticities are estimated to be rather low, especially for DI recipients, ranging from 0.1 to 0.3 (Kostol and Mogstad (2014); Koning and van Sonsbeek (2017); Ruh and Staubli (forthcoming)). Therefore, it appears unlikely that higher work incentives reduce program expenditures. [10]

Nevertheless, decreasing r can still have positive welfare effects even with increasing expenditures (since the insurance value increases in $1-r$). To obtain a money metric of the welfare derivative, we divide equation (4.10) by $u'(w-\tau)$ to get

$$\frac{\partial\tilde{W}}{\partial r} = \frac{\partial W/\partial r}{u'(w-\tau)} = \Delta\tau - \int_{\theta^A}^{\infty} p(\theta)y(\theta)\frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)}dF(\theta), \tag{4.13}$$

where

[10] The evaluation of the BOND experiment by Gubits et al. (2018) confirm as much. Even without induced entry, program expenditures increased.

$$\Delta\tau \equiv \underbrace{\frac{\partial\theta^A}{\partial r} f(\theta^A)p(\theta^A)\left[b - ry(\theta^A)\right]}_{\text{induced entry effect}} + \underbrace{\int_{\theta^A}^{\infty} p(\theta) r \frac{\partial y(\theta)}{\partial r} dF(\theta)}_{\Delta\text{labor supply}}. \tag{4.14}$$

As long as individuals are not fully insured already, i.e. $w - \tau > c^B(\theta^A)$, it holds that $u'(w-\tau) < u'(c^B(\theta^A))$. Hence, providing higher work incentives (decreasing r) is welfare improving ($\partial\tilde{W}/\partial r < 0$) if the labor supply effect compensates for the induced entry effect.

In general, we can rewrite (4.13) to see that the sign of the welfare effect $\partial\tilde{W}/\partial r \lesseqgtr 0$ is equivalent to[11]

$$\frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y(\theta)|DI]} \gtreqless -\varepsilon + \nu\left(\frac{b - ry(\theta^A)}{E[y(\theta)|DI]}\right), \tag{4.15}$$

where ν is the DI take-up semi-elasticity with respect to r defined as

$$\nu = -\frac{\partial \int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{\partial r} \frac{1}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} = \frac{\partial\theta^A}{\partial r} f(\theta^A)p(\theta^A)\frac{1}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}, \tag{4.16}$$

and $E[y(\theta)|DI]$ denotes the average earnings of DI recipients above SGA, defined by

$$E[y(\theta)|DI] = \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}, \tag{4.17}$$

and

$$E[y(\theta)\frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)}|DI] = \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}. \tag{4.18}$$

The LHS of (4.15) captures the consumption smoothing benefit of higher work incentives. To implement the LHS, we need to parametrize the utility function or use a Taylor approximation to obtain an expression only depending on the coefficient of relative risk aversion.

The RHS of (4.15) captures the fiscal effects. In principle, the RHS consists of estimable quantities. The only challenge is the DI take-up semi-elasticity ν. Therefore, we implicitly differentiate equation (4.7), which characterizes the marginal applicant, using

[11] Note that the sign of the inequality switches. That is $\partial\tilde{W}/\partial r < 0$ if the left-hand side (LHS) of (4.15) is *larger* than the right-hand side (RHS).

the equalities from (4.8) and 4.9) to show that

$$\frac{\partial \theta^A}{\partial r} = \frac{u'(c^B(\theta^A))y(\theta^A)}{h_\theta(z(\theta^A),\theta^A) - h_\theta(z^B(\theta^A),\theta^A)} = -\frac{\partial \theta^A}{\partial b} y(\theta^A) = -\frac{\partial \theta^A}{\partial SGA}\frac{y(\theta^A)}{r}. \tag{4.19}$$

Therefore, we can rewrite (4.15) as

$$\frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y(\theta)|DI]} \gtreqless -\varepsilon + \mu\left(\frac{b - ry(\theta^A)}{b}\right)\frac{y(\theta^A)}{E[y(\theta)|DI]}, \tag{4.20}$$

where μ is the benefit take-up elasticity with respect to b

$$\mu = \frac{\partial \int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{\partial b}\frac{b}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} = -\frac{\partial \theta^A}{\partial b} f(\theta^A)p(\theta^A)\frac{b}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}. \tag{4.21}$$

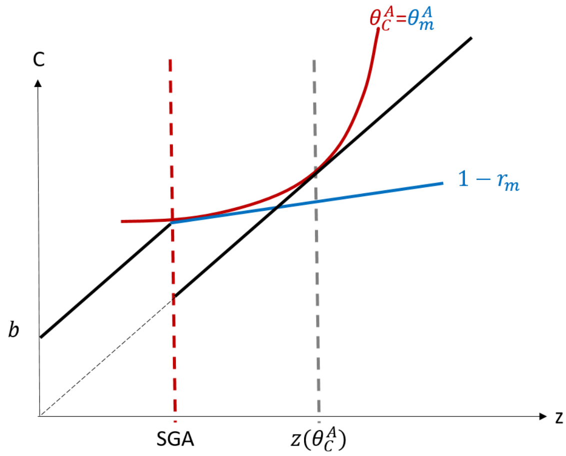
Therefore, the benefit take-up elasticity μ is a sufficient statistic for the induced entry effect. This elasticity is easier to estimate with reduced form methods since one does not rely on policies that change the benefit offset but only the DI benefit level. Consequently, increasing (decreasing) the offset rate increases welfare if the LHS of equation (4.20) is larger (smaller) than the RHS.

4.2.3 Moving from Cash Cliff to Benefit Offset

Section 4.2.2 developed a sufficient statistic formula to evaluate the local optimality of the offset rate r. However, most DI programs feature cash cliffs and not benefit offset schemes. The relevant policy discussion, therefore, is whether a cash cliff should be replaced by a benefit offset. The key idea to our approach is that a cash cliff can be modelled as a benefit offset.

Figure 4.2 illustrates how we construct a hypothetical benefit offset that mirrors a cash cliff. The black line represents the budget set of a DI recipient. The black dotted line marks the budget set of non-recipients. The red line is the indifference curve of the marginal DI applicant in the cash cliff regime with disability θ_C^A. Every individual with a lower θ does not apply for DI. Everyone with a higher θ works at or below the earnings exempt SGA. The blue line marks the budget set of a hypothetical benefit offset regime.The hypothetical benefit offset has an offset rate $1 - r_m$, which is equivalent to the slope of the indifference curve of the marginal applicant at the cash cliff. Hence, this hypothetical benefit offset system has the same marginal applicant as the cash cliff regime (i.e. $\theta_m^A = \theta_C^A$). For types with higher disability degree θ than the marginal applicant, the incentives to work and apply to DI are exactly the same. For types with lower θ than the marginal applicant, there is no difference between the two DI programs either.

FIGURE 4.2. EQUIVALENCE BETWEEN CASH CLIFF AND BENEFIT OFFSET.



Note: This figure illustrates the benefit offset scheme which is equivalent to the cash cliff system. The benefit offset is determined by $1 - r_m = \frac{h_z(SGA, \theta_C^A)}{u'(b+SGA)}$. C denotes disposable income and z is labor income.

Replacing a cash cliff with a benefit offset is, therefore, equivalent to increasing labor supply incentives starting from this hypothetical benefit offset. To evaluate the welfare effects of a benefit offset introduction, we conduct the opposite thought experiment of moving from a benefit offset to cash cliff scheme, i.e. moving from a benefit offset with work incentives $r < r_m$ closer to r_m. This way we can start with $r = r_m - \epsilon$ (with $\epsilon > 0$) and consider the limiting case $\epsilon \to 0$. For all $\epsilon > 0$, we have an interior marginal applicant supplying more labor than SGA and can use the analysis from Section 4.2.2. That is, we need to evaluate (4.20) for $r \to r_m$. This yields a much simpler sufficient statistic formula. Condition (4.20) becomes

$$\frac{u'(b + SGA) - u'(w - \tau)}{u'(w - \tau)} \gtreqless -\varepsilon + \mu. \tag{4.22}$$

This is a powerful result. First, equation (4.22) implies that welfare increases with the introduction of a benefit offset regime with minimal labor incentives whenever the LHS is larger than the RHS. Second, this test might even be informative on whether there exists a welfare-improving benefit offset at all, if the welfare function was concave in r.

Derivation We lined out the key idea and result. Subsequently, we show these insights formally. Welfare under a cash cliff system is given by

$$\begin{aligned}W^C =& u(w-\tau^C) + \int_0^{\theta_C^A} u(z(\theta)) - h(z(\theta),\theta) dF(\theta) \\ &+ \int_{\theta_C^A}^{\infty} p(\theta) \left[u(c^C(\theta)) - h(z^C(\theta),\theta)\right] dF(\theta) \\ &+ \int_{\theta_C^A}^{\infty} [1-p(\theta)] \left[u(z(\theta)) - h(z(\theta),\theta)\right] dF(\theta).\end{aligned} \tag{4.23}$$

The government's budget constraint is denoted by

$$\tau^C = \int_{\theta_C^A}^{\infty} p(\theta) b \mathbb{1}\{z^C(\theta) \le SGA\} dF(\theta) = \int_{\theta_C^A}^{\infty} p(\theta) b dF(\theta). \tag{4.24}$$

Consumption is given by

$$c^C(\theta) = \begin{cases} b + z^C(\theta), & \text{if } z^C(\theta) \le \text{SGA} \\ z^C(\theta), & \text{if } z^C(\theta) > \text{SGA}. \end{cases} \tag{4.25}$$

The marginal applicant θ_C^A is unique and determined by

$$u(b+SGA) - h(SGA, \theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A), \theta_C^A), \tag{4.26}$$

where $z(\theta_C^A)$ solves

$$u'(z(\theta_C^A)) = h_z(z(\theta_C^A), \theta_C^A). \tag{4.27}$$

Proposition 1. *The introduction of a benefit offset scheme with offset r either i) has no effect at all or ii) incentivizes more labor supply of DI recipients but also induces more entry into DI. Hence, a benefit offset scheme with a positive labor supply effect always induces entry.*

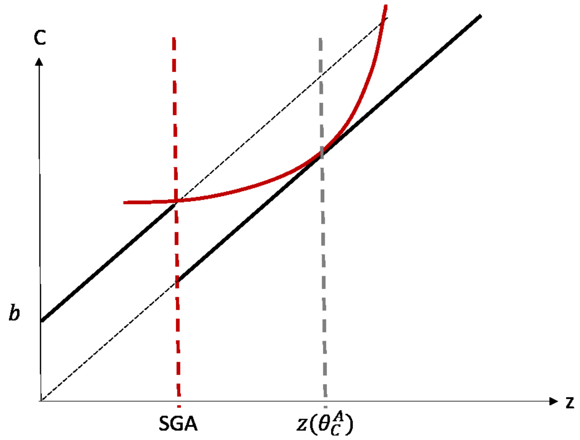
i) If $1-r \le \bar{IK}$ where $\bar{IK}$ is the slope of the indifference curve of the marginal applicant under the cash cliff at the SGA, i.e. $\bar{IK} := \frac{h_z(SGA,\theta_C^A)}{u'(b+SGA)}$, there is no labor supply effect and no induced entry effect of introducing a benefit offset scheme.

ii) If $1-r > \bar{IK}$, there is a positive labor supply effect but also a positive induced entry effect.

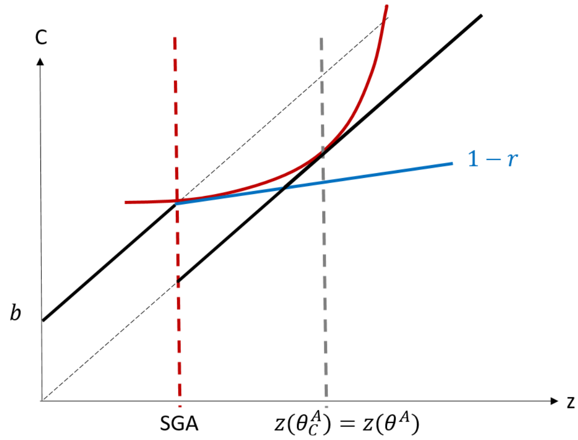
Proof. see Appendix 4A □

FIGURE 4.3. INDUCED ENTRY AND LABOR SUPPLY EFFECTS

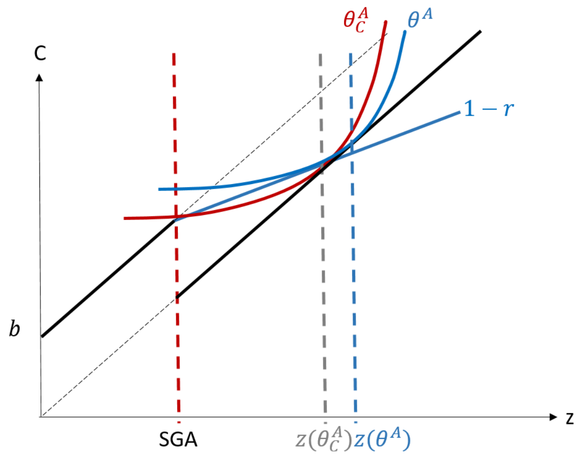
(A). CASH CLIFF.



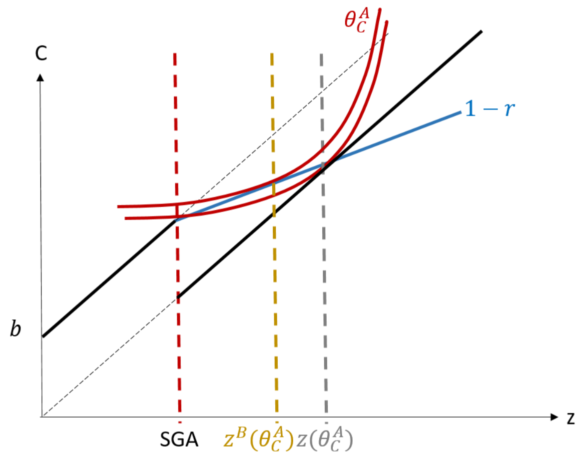
(B). BENEFIT OFFSET WITHOUT ENTRY.



(C). BENEFIT OFFSET WITH ENTRY—INDUCED ENTRY EFFECT.



(D). BENEFIT OFFSET WITH ENTRY—LABOR SUPPLY EFFECT.



Note: This figure illustrates Proposition 1. Panel 4.3c depicts the induced entry effect by showing that the marginal applicant changes. Panel 4.3d depicts the labor supply effect of the previous marginal applicant, increasing labor supply from SGA to $z^B(\theta_C^A)$.

Lemma 1. *Equivalence between benefit offset and cash cliff*

i) There exists a benefit offset schedule (b, r_m, SGA) *with* $1 - r_m = \frac{h_z(SGA,\theta_C^A)}{u'(b+SGA)}$, *which is equivalent to the cash cliff regime* (b, SGA), *i.e.* $\theta^A = \theta_C^A$ *and* $z^B(\theta) = z^C(\theta)\ \forall\theta$.

ii) To evaluate the marginal welfare effect of a benefit offset policy, we can study a marginal change in r *starting from* r_m.

Proof. see Appendix 4A □

We now study the effect of moving from a cash cliff to a benefit offset program. To do so, we analyze the opposite change, i.e. moving from a benefit offset with work incentives

$r < r_m$ closer to r_m being equivalent to a cash cliff scheme. This way, we can start with $r = r_m - \epsilon$ with $\epsilon > 0$ and let $\epsilon \to 0$. For all $\epsilon > 0$, there is an interior marginal applicant. The analysis in Section 4.2.2 showed that, to get a hold of the welfare effect, we need to evaluate (4.20).

$$\frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y(\theta)|DI]} \gtreqless -\varepsilon + \mu\left(\frac{b - ry(\theta^A)}{b}\right)\frac{y(\theta^A)}{E[y(\theta)|DI]}, \tag{4.28}$$

where $y(\theta^A)$ denotes the earnings above the earnings disregard, i.e.

$$y(\theta) = \begin{cases} z^B(\theta) - SGA, & \text{if } z^B(\theta) \geq \text{SGA} \\ 0, & \text{if } z^B(\theta) < \text{SGA}. \end{cases} \tag{4.29}$$

For $r \to r_m$, it holds that $\theta^A \to \theta^A_C$, $y(\theta^A) \to 0$.

We can bound the numerator on the LHS with

$$\begin{aligned} \frac{u'(c^B(\theta^A)) - u'(w-\tau)}{u'(w-\tau)}E[y(\theta)|DI] &\leq E[y(\theta)\frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)}|DI] \\ &\leq \frac{u'(b + SGA) - u'(w-\tau)}{u'(w-\tau)}E[y(\theta)|DI], \end{aligned} \tag{4.30}$$

by concavity of $u()$. By the sandwich theorem, it thus holds that

$$\lim_{\epsilon \to 0} \frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y|DI]} = \frac{u'(b + SGA) - u'(w-\tau)}{u'(w-\tau)}, \tag{4.31}$$

since $\lim_{\epsilon\to 0} y(\theta^A) = 0$.

For the RHS, it holds that

$$\lim_{\epsilon \to 0}\left(\frac{b - ry(\theta^A)}{b}\right) = 1, \tag{4.32}$$

and

$$\frac{y(\theta^A)}{E[y(\theta)||DI]} \geq 1. \tag{4.33}$$

Note that $\frac{y(\theta^A_B)}{E[y(\theta)|DI]}$ is increasing in ϵ because

$$\frac{\partial}{\partial r}\frac{y(\theta^A)}{E[y(\theta)|DI]} = \frac{\frac{\partial y(\theta^A)}{\partial r}E[y(\theta)|DI] - \frac{\partial E[y|DI]}{\partial r}y(\theta^A)}{E[y(\theta)|DI]^2} > 0 \tag{4.34}$$

$$\leftrightarrow$$

$$\frac{\partial y(\theta^A)}{\partial r}\frac{r}{y(\theta^A)} > \frac{\partial E[y(\theta)|DI]}{\partial r}\frac{r}{E[y(\theta)|DI]} \tag{4.35}$$

$$\leftrightarrow$$

$$\varepsilon_{marginal} > \varepsilon_{average}. \tag{4.36}$$

Therefore, $\frac{y(\theta^A)}{E[y(\theta)|DI]}$ is monotonically decreasing for $r \rightarrow r_m$, and therefore

$$\lim_{\epsilon \rightarrow 0}\frac{y(\theta^A)}{E[y(\theta)|DI]} = \inf\{\frac{y(\theta^A)}{E[y(\theta)|DI]}\} = 1. \tag{4.37}$$

All together, we need to evaluate

$$\frac{u'(b + SGA) - u'(w - \tau)}{u'(w - \tau)} \geq -\varepsilon + \mu \tag{4.38}$$

for the marginal introduction of a benefit offset.

4.2.4 Extensions

Our insights presented above are derived in a stylized model. In Appendix 4B, we show that our results generally hold for: (1) any convex preferences with single crossing (as compared to separability of utility from consumption and disutility of work), (2) the presence of application costs to the DI program, (3) benefit substitution (i.e. the presence of other welfare programs), (4) labor adjustment costs, (5) other sources of heterogeneity (e.g. skill heterogeneity causing wage heterogeneity), and (6) one-period structure with taxes. The intuition for the robustness of our results is that we exploit envelope conditions to derive the welfare effects in terms of elasticities. The exact model specifications make some behavioral responses more and less elastic. Since, we estimate the elasticities with reduced form techniques, we do not need to know the exact model specifications. For instance, the presence of DI application costs could make the application decision less sensitive to financial incentives, which would show up in a lower DI benefit take-up elasticity estimate.

4.3 Welfare Implications

As the empirical analysis is in process, we provide a first rough implementation of our sufficient statistic formulas for the United States. Thus, this section is merely for illustration purpose. Section 4.4 describes the planned empirical implementation for Canada.

The result of the theoretical model in Section 4.2.3 has shown that one can evaluate, how abolishing a cash cliff in favor of a benefit offset affects welfare, by estimating the quantities in the following equation

$$\frac{u'(b + SGA) - u'(w - \tau)}{u'(w - \tau)} \gtreqless -\varepsilon + \mu, \tag{4.39}$$

where b denotes the DI benefit level, SGA the earnings disregard (location of the cash cliff), w labor income in the first period (without disability), τ the lump sum taxes levied in the first period, ε the earnings elasticity, and μ the benefit take-up elasticity with respect to b.

Implementation of the LHS For the LHS, we use a quadratic approximation of the utility function to get[12]

$$\frac{u'(b + SGA) - u'(w - \tau)}{u'(w - \tau)} \approx \gamma \frac{w - \tau - (b + SGA)}{w - \tau} = \gamma \left(1 - \frac{b + SGA}{w - \tau}\right), \tag{4.40}$$

where $\gamma = -\frac{u''(w-\tau)}{u'(w-\tau)}(w - \tau)$ is the coefficient of relative risk aversion evaluated at $w - \tau$. Hence, we need an estimate of the replacement rate for the marginal DI applicant, i.e. $(b+SGA)/(w-\tau)$. In the model, we rule out savings resulting in consumption being equal to income. However, the LHS should capture the consumption drop and not the income drop. Meyer and Mok (2018) study the income and consumption patterns of individuals reporting disabilities in the United States. They find that individuals reporting a chronic and severe disability face an after-tax post-transfer income drop of 30 percent ten years after onset of the condition. Consumption reacts less. Hence, focusing on income can be seen as an upper bound. Ideally, we would know the consumption drop of the marginal applicant. We want to exploit this more in the empirical implementation for Canada,

[12] This is a standard approach, see Chetty and Finkelstein (2013).

where we might explore financial well-being and distress. For the time being, we use the income drop of 30 percent from Meyer and Mok (2018), i.e. $1 - \frac{b+SGA}{w-\tau} = 1 - 0.7 = 0.3$.[13]

Implementation of the RHS For the RHS, we need estimates for the DI take-up elasticity with respect to benefits μ and the earnings elasticity of DI recipients ε.

The take-up elasticity has not been directly estimated in the literature. Thus, we have to employ estimates of the *application* elasticity with respect to benefits and take award rates into account. To obtain an upper bound of the take-up elasticity, we multiply the application elasticity with the average award rate. This gives an upper bound, since individuals, who actually react to the benefits (marginal applicants), should have lower than average award rates. First, Low and Pistaferri (2015, Table 7) report empirical estimates of the application benefit elasticity that range from 0.2 to 1.3 in the United States. Low and Pistaferri (2015)'s model implies an application benefit elasticity of 0.62. Second, French and Song (2014) find an award rate after 10 years from the initial application of 0.67 for the United States. Hence, we get a take-up elasticity μ ranging from 0.1 to 0.9.

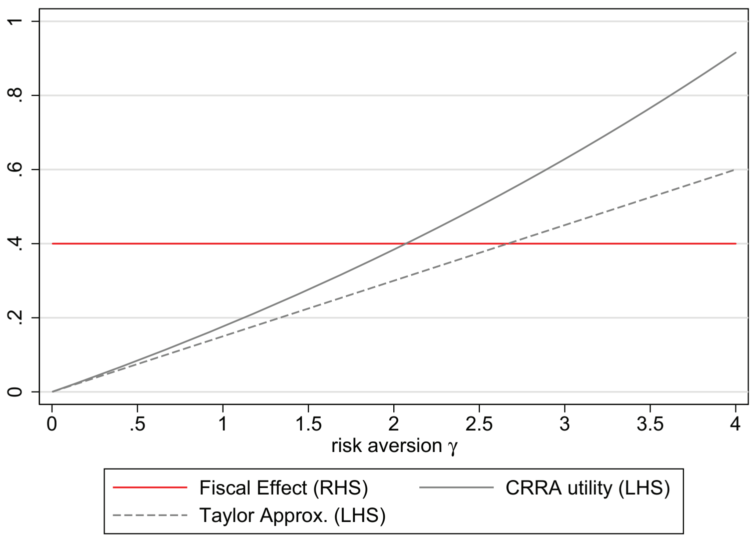
We are not aware of a direct estimate of the earnings elasticity of the marginal DI applicant for the United States. Ruh and Staubli (forthcoming) exploit bunching at the cash cliff in Austria and estimate an earnings elasticity of 0.27. Koning and van Sonsbeek (2017) report an elasticity of 0.12 for the Netherlands. Kostol and Mogstad (2014) find elasticity estimates between 0.1 and 0.3 for Norway. Evidence from the benefit field experiment in the United States indicates that the labor supply elasticity might be rather low (Weathers and Hemmeter, 2011; Gubits et al., 2018). Therefore, we use $\varepsilon = 0.1$.

Results Figure 4.4 illustrates the fiscal (RHS) and consumption smoothing effect (LHS) of introducing a benefit offset as a function of risk aversion. If the consumption smoothing benefits (red line) exceed the fiscal costs (gray lines), replacing the cash cliff with a benefit offset is welfare improving. We plot the fiscal effect for the largest ($\mu = 0.9$, dashed gray line) and smallest ($\mu = 0.1$, solid gray line) benefit take-up elasticity reported in the literature. For the smallest μ, introducing a benefit offset is welfare improving for all levels of risk aversion. For the highest μ, introducing a benefit offset is only welfare

[13] Autor and Duggan (2003, Table 1) report lower DI replacement rates. However, this replacement rate is before additional labor income from working up to the SGA, i.e. $b/(w-\tau)$ rather than $(b+SGA)/(w-\tau)$.

improving if risk aversion is rather large ($\gamma > 2.6$). Hence, for reasonable values of risk aversion it is better to keep a cash cliff regime.

FIGURE 4.4. WELFARE IMPLICATIONS.



Note: If the consumption smoothing effect (Cons. Smoothing) exceeds the fiscal costs (Budget Effect), introducing a benefit offset is welfare improving.

4.4 Empirical Implementation with Canadian Data

In this section, we report our empirical approach to implementing our sufficient statistics formula for Canada. We cannot show results yet, as we just gained access to the administrative data.

Framework In this empirical analysis, we plan to estimate the effects of changes in the level of DI benefits and the earnings disregard on program entry and exit, labor supply, and financial well-being in Canada. This allows us to infer the earnings elasticity and benefit take-up elasticity with respect to the benefit level, which are the crucial parameters to implementing our sufficient statistics formula.

Studying the Canadian case will offer lessons for other programs serving similar populations. Moreover, estimating the behavioral response to changes in DI parameters has been difficult in the United States, because individuals largely face identical program rules making suitable counterfactuals difficult to find (Staubli, 2011). Canada, on the other hand, operates two distinct DI programs for Quebec and the Rest of Canada (RoC). We can exploit exogenous variation in program parameters that is generated by two reforms to the Canadian Pension Plan DI program (CPP-D) that left the Quebec Pension Plan DI program (QPP-D) unchanged. The first reform took place in 1987 and increased the replacement rate of DI benefits by about 36 percent in RoC (Gruber, 2000). The second reform was implemented in 2001 and increased the earnings disregard in the CPP-D to CAD 3,800 per year (Campolieti and Riddell, 2012). As already mentioned, these reforms were not implemented in Quebec enabling us to use the population of Quebec as a control group in this quasi-experiment.

Data We recently received approval from Statistics Canada to work with the Canadian Longitudinal Administrative Database (LAD) in the Research Data Center at the University of Calgary. The LAD contains detailed information of 20 percent of individuals (and their spouse and children) filing an income tax return between 1982 and 2016. Importantly for our context, the LAD also contains information on the receipt of DI benefits, demographics, earnings, income, other government transfers, savings, taxes, and housing. Due to the detailed information on income and savings flows, we can study how changes in DI generosity not only affect labor supply and DI claiming, but also the social insurance provided by taxes and transfers.

Methods We will exploit exogenous variation in DI benefit levels and the earnings disregard caused by two policy reforms to the CPP-D in 1987 and 2001.

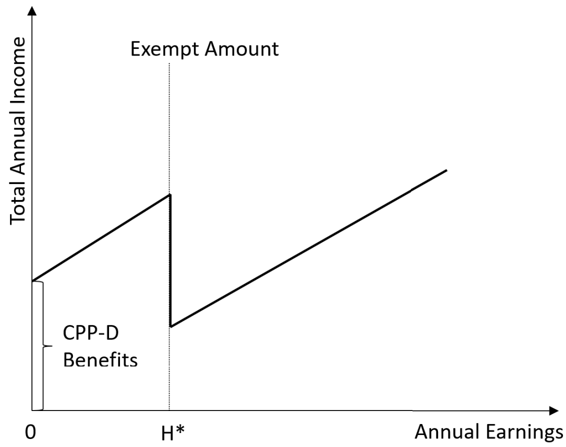
The 1987 CPP-D reform: Prior to 1987, the CPP-D pension was substantially less generous than the QPP-D pension. In an effort to align the two programs, the government increased the CPP-D pension in 1987 to the level of the QPP-D pension. This change increased the CPP-D pension by almost CAD 2,000 per year, corresponding to an average increase in the replacement rate of 36 percent (Gruber, 2000). We use a difference-in-differences (DiD) identification strategy to estimate the causal effects of this reform. Specifically, we compare the change in an outcome variable, for example earnings, in RoC with the change in the same outcome variable in Quebec before and after the reform. This comparison can be implemented with the following regression

$$y_{ijt} = \alpha + \beta T_{ijt} + \theta_j + \pi_t + X'_{ijt}\delta + \epsilon_{ijt}, \tag{4.41}$$

where y_{ijt} is an outcome variable of individual i living in province j in year t, T_{ijt} is a dummy that is equal to 1 if an individual lives in RoC after the reform, θ_j are province fixed effects, π_t are year fixed effects, and X_{ijt} is a vector of demographic and labor market characteristics (e.g. socioeconomic status, age, experience, or previous earnings). The coefficient of interest is β, which identifies the effect of the 1987 benefit increase on y_{ijt} under the assumption that trends in y_{ijt} would have been the same in RoC and Quebec in the absence of the reform. Using program entry and exit as outcome variables allows us to estimate the benefit take-up elasticity with respect to the benefit level. Analyzing the effect on earnings provides insights on the earnings elasticity. Apart from the implementation of our sufficient statistics formula, we will also contribute to the literature in analyzing the effects of the 1987 CPP-D reform in detail. Gruber (2000) studies the effect of the same reform on labor force non-participation, while we will provide novel evidence on the effects on DI exit and entry, government transfers, and other financial outcomes such as savings and housing. Additionally, we will carefully investigate the validity of the "parallel trends" assumption. Lastly, we can zoom in to the border of Quebec and RoC similar to Campolieti and Riddell (2012) to have a more homogeneous sample in which the concern about non-parallel trends is likely to be less prevalent.

The 2001 CPP-D reform: In June 2001, the CPP-D introduced an annual earnings exemption allowing beneficiaries to earn up to CAD 3,800 without having their benefits suspended. The purpose of this policy was to encourage work among CPP-D beneficiaries. We apply two estimation strategies to examine the effect of the earnings exemption. The first strategy is a bunching estimator, which exploits the discontinuity in the implicit tax on work at the exempt threshold of CAD 3,800 (cash cliff). Specifically, the exempt amount causes a notch in the budget constraint in a static labor supply model, defined as a discrete increase in the (implicit) tax liability (Ruh and Staubli, forthcoming). This notch displayed in Figure 4.5 creates a strong incentive for DI beneficiaries to keep their earnings just below the exempt threshold. This type of behavior is coined "bunching" and, as (Saez, 2010) shows, the amount of bunching can be used to estimate an earnings elasticity with respect to the net-of-tax rate. This parameter is crucial to assess the effectiveness of return-to-work programs and to implement our sufficient statistics model (Ruh and Staubli, forthcoming). The second strategy is a DiD approach similar to the one shown in equation (4.41). Specifically, we compare the change in an outcome variable in RoC with the change in the same outcome variable in Quebec before and after the introduction of the earnings exemption in 2001. Campolieti and Riddell (2012) also study the 2001 reform, but they do not examine effects on beneficiaries' earnings, government transfers, and other financial outcomes.

FIGURE 4.5. BUDGET CONSTRAINT UNDER CPP-D AFTER THE 2001 REFORM.



Note: This illustration corresponds to Figure 4.1a in the theoretical part in Section 4.2. H^* marks the earnings exemption (exempt amount) corresponding to SGA in the theoretical part. CPP-D benefits is the level of flat DI benefits labeled by b in Section 4.2.

4.5 Conclusions

The past decades featured a significant increase in the share of individuals receiving disability insurance (Autor et al., 2018). Together with the number of individuals receiving DI, the program costs have sky-rocketed. Hence, reducing program costs has appeared both on the policy makers' and economists' agendas. One possibility to limit this expansion is improving financial work incentives for DI recipients. Most DI programs consist of two important parameters: the level of DI benefits and the earnings disregard quantifying the amount of earnings DI recipients can earn before benefits are deducted. Under a cash cliff regime, DI recipients lose their entire DI cash benefits if their earnings surpass the earnings disregard posing as major work disincentive (Autor and Duggan, 2003; Bound et al., 2010). Reducing DI cash benefits continuously beyond the earnings disregard by introducing a benefit offset may increase work incentives. This could induce DI recipients with substantial remaining work capacity to increase labor supply (labor supply effect). However, the more generous DI program might cause more DI take-up (induced entry effect) and increase program costs.

In this paper, we develop a sufficient statistics model that allows us to estimate the welfare effects of replacing a cash cliff with a benefit offset system. The model points out that this evaluation crucially depends on two sufficient statistics: the earnings elasticity of DI recipients, and the DI benefit take-up elasticity. The two elasticities are sufficient in the sense that they entirely capture the labor supply effect, i.e. DI recipients increasing their labor supply, and the induced entry effect, i.e. more individuals applying for DI. The model contributes to the existing literature in two ways. First, it provides simple yet robust sufficient statistics formulas to evaluate the welfare effects of introducing a benefit offset. Second, it sheds light on the potential size of the induced entry effect based on credible reduced form estimates.

In an empirical application of our model, we plan to estimate these two sufficient statistics exploiting two policy reforms in Canada that changed the level of DI benefits and the earnings exempt. As this is work in progress, we evaluate the welfare effects of introducing a benefit offset scheme with estimates from previous studies. With estimates for the United States, we find that it is unlikely that the introduction of a benefit offset scheme reduces program expenditures if the benefit take-up elasticity is high. This is in line with the findings from the BOND field experiment recently conducted in the United States (Gubits et al., 2018). If the benefit take-up elasticity is sufficiently low, our formula suggests that the introduction of a benefit offset is welfare improving. This shows the crucial importance of credibly estimating the benefit take-up elasticity. We aim at providing these credible estimates with our empirical approach for Canada.

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Appendix

4A Proofs

Proof. Proposition 1

Note that if the marginal applicant of the cash cliff scheme does not adjust her labor supply under the benefit offset scheme, then all θ-types receiving DI benefits do not adjust their labor supply either. Hence, to determine whether there is a positive labor supply effect it is sufficient to only look at the labor supply response of the marginal applicant θ_C^A.

Under the cash cliff system (b, SGA), the marginal applicant θ_C^A is determined by

$$u(b + SGA) - h(SGA, \theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A), \theta_C^A), \tag{4.42}$$

and thus it has to hold that

$$u(b + SGA) - h(SGA, \theta) > u(z(\theta)) - h(z(\theta), \theta), \ \forall \theta > \theta_C^A. \tag{4.43}$$

After the benefit offset scheme(b, r, SGA) is introduced, the marginal applicant under the cash cliff system θ_C^A solves

$$z^B(\theta_C^A) := \operatorname*{argmax}_{z \geq SGA} u(c^B(\theta_C^A)) - h(z, \theta_C^A), \tag{4.44}$$

with

$$c^B(\theta_C^A) = \begin{cases} b + z^B(\theta_C^A), & \text{if } z^B(\theta_C^A) \leq SGA \\ b + SGA + (1-r)(z^B(\theta_C^A) - SGA), & \text{if } z^B(\theta_C^A) > SGA. \end{cases} \tag{4.45}$$

Hence, an interior solution with more labor supply by the marginal applicant θ_C^A solves

$$(1-r)u'(b + SGA + (1-r)(z^B(\theta_C^A) - SGA)) = h_z(z^B(\theta_C^A), \theta_C^A) \tag{4.46}$$

and therefore

$$1 - r > \frac{h_z(SGA, \theta_C^A)}{u'(b + SGA)} \quad \Leftrightarrow \quad z^B(\theta_C^A) > SGA. \tag{4.47}$$

Moreover, we have no labor supply effect $z^B(\theta_C^A) = SGA$ if $1-r \leq \frac{h_z(SGA,\theta_C^A)}{u'(b+SGA)}$. If there is no labor supply effect, then the application decision is still the same as in the cash cliff regime and therefore there is no entry effect. Contrary, if there is a labor supply effect then there is a positive entry effect as well. Let us denote the marginal applicant under the benefit offset system θ^A. Suppose, $z^B(\theta_C^A) > SGA$ but $z^B(\theta_C^A) > z^B(\theta^A) \Leftrightarrow z(\theta_C^A) > z(\theta^A) \Leftrightarrow \theta_C^A < \theta^A$. Then, we have $u(b+SGA) - h(SGA, \theta^A) > u(z(\theta^A)) - h(z(\theta^A), \theta^A)$ by (4.43). $\lightning$ Suppose

$z^B(\theta_C^A) > SGA$ and $z^B(\theta_C^A) = z^B(\theta^A) \Leftrightarrow z(\theta_C^A) = z(\theta^A) \Leftrightarrow \theta_C^A = \theta^A$. Then, we have $u(b+SGA) - h(SGA, \theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A), \theta_C^A) = u(b+SGA+r(z^B(\theta_C^A) - SGA)) - h(z^B(\theta_C^A), \theta_C^A)$ but this only holds for $z^B(\theta_C^A) = SGA$. ↯ Hence, a positive labor supply effect $z^B(\theta_C^A) > SGA$ implies a positive entry effect $\theta_C^A > \theta^A$. □

Proof. Lemma 1

i) The marginal applicant θ^A of the benefit offset scheme with (b, r_m, SGA) is determined by

$$u(b + SGA + (1 - r_m)(\underbrace{z^B(\theta^A) - SGA}_{\equiv y(\theta^A)})) - h(z^B(\theta^A), \theta^A)$$
$$= u(z(\theta^A)) - h(z(\theta^A), \theta^A). \tag{4.48}$$

where $z^B(\theta^A)$ solves

$$(1 - r_m)u'(b + SGA + (1 - r_m)(z^B(\theta^A) - SGA)) = h_z(z^B(\theta^A), \theta^A) \tag{4.49}$$

and $z(\theta^A)$ solves

$$u'(z(\theta^A)) = h_z(z(\theta^A), \theta^A) \tag{4.50}$$

By $1 - r_m := \frac{h_z(SGA, \theta_C^A)}{u'(b+SGA)}$, (4.49) holds if $\theta^A = \theta_C^A$ and $z^B(\theta^A) = SGA$. Uniqueness of the marginal applicant implies that this is the only solution.

$z^B(\theta) = z^C(\theta)\ \forall\theta$ holds, because for all individuals with $z^C(\theta) < SGA$ nothing changes. Moreover, all individuals that bunch at the earnings disregard under the cash cliff system (i.e. $\theta > \theta^A (= \theta_C^A)$ and $z^C(\theta) = SGA$) still bunch at SGA under the benefit offset regime as $(1 - r_m)u'(b + SGA + (1 - r_m)y(\theta)) < h_z(z^B(\theta), \theta)$.

ii) Follows immediately from i). As all outcomes are the same, welfare is the same.

□

Lemma 2. *Marginal Applicants*

i) θ_C^A is unique and determined by

$$u(b + SGA) - h(SGA, \theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A), \theta_C^A). \tag{4.51}$$

This implies $z^C(\theta_C^A) = SGA$ and $z^C(\theta_C^A) < z(\theta_C^A)$.

ii) θ^A is unique and determined by

$$u(b + SGA + (1 - r)(z^B(\theta^A) - SGA)) - h(z^B(\theta^A), \theta^A)$$
$$= u(z(\theta^A)) - h(z(\theta^A), \theta^A). \tag{4.52}$$

where $z^B(\theta^A)$ *solves*

$$(1-r)u'(b+SGA+r(z^B(\theta^A)-SGA)) = h_z(z^B(\theta^A),\theta^A) \tag{4.53}$$

and $z(\theta^A)$ *solves*

$$u'(z(\theta^A)) = h_z(z(\theta^A),\theta^A). \tag{4.54}$$

Moreover, we have $SGA \leq z^B(\theta^A) < z_K$*, where* z_K *is the intersection of the benefit offset and the regular budget set (i.e.* $b+SGA+(1-r)(z_K-SGA) = z_K$*), and* $z^B(\theta^A) < z(\theta^A)$*.*

Proof. Lemma 2

i) By definition

$$\theta_C^A := \inf\{\theta | u(c^C(\theta)) - h(z^C(\theta),\theta) > u(z(\theta)) - h(z(\theta),\theta)\}. \tag{4.55}$$

Suppose $z^C(\theta_C^A) > SGA$. Then, $c^C(\theta_C^A) = z^C(\theta_C^A)$ and $z^C(\theta_C^A) = z(\theta_C^A)$. Hence, $\theta_C^A \notin \{\theta | u(c_C(\theta)) - h(z_C^*(\theta),\theta) > u(z(\theta)) - h(z(\theta),\theta)\}$.↯

Suppose $z_C^*(\theta_C^A) < SGA$. Then, $\exists \varepsilon > 0$ such that $\bar{\theta} := \theta_C^A - \varepsilon < \theta_C^A$ and $z^C(\theta_C^A) < z^C(\bar{\theta}) < SGA$. Hence, $z^C(\bar{\theta})$ is the interior solution to $\max_{z\geq 0} u(b+z) - h(z,\bar{\theta})$. Therefore, $\bar{\theta} \in \{\theta | u(c^C(\theta)) - h(z^C(\theta),\theta) > u(z(\theta)) - h(z(\theta),\theta)\}$ but $\bar{\theta} < \theta_C^A$. ↯

Therefore, we must have $z^C(\theta_C^A) = SGA$ and θ_C^A is determined by

$$u(b+SGA) - h(SGA,\theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A),\theta_C^A). \tag{4.56}$$

Moreover, θ_C^A is unique because of single crossing of indifference curves of different θ-types (this is due to $h_{\theta z} > 0$).

ii) In case that $z^B(\theta^A) < SGA$, the proof is analogous to i). Hence, this proof is for interior marginal applicants (i.e. $z^B(\theta^A) \geq SGA$) only. First, we show that $SGA \leq z^B(\theta^A) < z_K$. For $SGA \leq z^B(\theta^A)$, the same argument applies as in i). If we had $z^B(\theta^A) \geq z_K$, individuals could reduce labor supply and increase earnings by leaving DI.

Therefore, θ^A is determined by

$$u(b+SGA+(1-r)(z^B(\theta^A)-SGA)) - h(z^B(\theta^A),\theta^A) = u(z(\theta_B^A)) - h(z(\theta^A),\theta^A) \tag{4.57}$$

where $z^B(\theta^A)$ solves

$$(1-r)u'(b+SGA+(1-r)(z^B(\theta^A)-SGA)) = h_z(z^B(\theta^A),\theta^A) \tag{4.58}$$

and $z(\theta^A)$ solves

$$u'(z(\theta^A)) = h_z(z(\theta^A), \theta^A). \tag{4.59}$$

Now suppose θ_1 and θ_2 satisfy equations (4.57)-(4.59). Then, (4.59) immediately implies $\theta_1 = \theta_2$. Hence, θ^A is unique.

□

4B Model Extensions

Our results from the baseline model discussed in the main part of this paper generally hold for several extensions: (1) convex preferences with single crossing (as compared to separability of consumption and disutility of work), (2) presence of application costs to the DI program, (3) benefit substitution (presence of other welfare programs), (4) adjustment costs to changing labor supply, (5) other sources of heterogeneity, and (6) one-period structure with taxes. With exemptions, every extension discussed in this Appendix follows the same structure. First, we point out the difference between the standard case and the extension. Second, we show that the sufficient statistics formula to find the optimal offset rate r still holds. Third, we show that the sufficient statistics formula regarding an introduction of a benefit offset scheme instead of a cash cliff system still applies.

Convex Preferences (Non-Separability of Consumption and Disutility of Work)

All derivations for the optimal benefit offset r do not rely on the separability of consumption and disutility of work. All formulas are generally valid for any convex preferences with single crossing of indifference curves for different θ-types. A generic utility function fulfilling these conditions could be $U(\theta) = U(c(z(\theta)), z(\theta), \theta)$. All results from the main part still hold, but the notation becomes slightly more cumbersome (i.e. $u'(c)$ becomes $U_c(c, z, \theta)$, $h_z(z, \theta)$ becomes $U_z(c, z, \theta)$, and $h_\theta(z, \theta)$ becomes $U_\theta(c, z, \theta)$). The intuition for the robustness to non-separability is that our results rely on envelope conditions, i.e. that behavioral responses of individuals do not have first order welfare effects. Our results do not exploit the functional form of the utility function.

Application Costs

Setup: In this extension, we consider disability application costs $\psi > 0$. We only consider application costs that are low enough such that at least some individuals still apply for disability insurance (i.e. $\exists \theta^{max} \leq \infty$ s.t. $\psi = u(c^B(\theta^{max})) - h(z^B(\theta^{max}), \theta^{max}) - u(z(\theta^{max})) - h(z(\theta^{max}), \theta^{max})$). Individuals with disutility of labor θ choose their labor supply $z(\theta) \geq 0$ by maximizing

$$z(\theta) := \underset{z \geq 0}{\operatorname{argmax}}\, u(c(z)) - h(z, \theta), \tag{4.60}$$

where $c(z) = z$. Under a benefit offset scheme (b, r, SGA), individuals with disutility of labor θ choose their labor supply $z^B(\theta) \geq 0$ by maximizing

$$z^B(\theta) := \underset{z \geq 0}{\operatorname{argmax}}\, u(c^B(z)) - h(z, \theta), \tag{4.61}$$

where

$$c^B(\theta) = \begin{cases} b + z^B(\theta), & \text{if } z^B(\theta) \leq SGA, \\ b + SGA + (1-r)(z^B(\theta) - SGA), & \text{if } z^B(\theta) > SGA. \end{cases} \tag{4.62}$$

These are exactly the same as in the standard model. The only difference to the standard case is that individuals choose to apply for DI if

$$u(z(\theta)) - h(z(\theta),\theta) \leq u(c^B(\theta)) - h(z(\theta),\theta) - \frac{\psi}{p(\theta)}. \tag{4.63}$$

Note that the single crossing condition is still fulfilled as the LHS of inequality (4.63) decreases in θ while the right-hand side increases in θ. Particularly, the "relative application costs" $\psi/p(\theta)$ decrease in θ. Consequently, the unique marginal applicant is now determined by

$$u(z(\theta^A)) - h(z(\theta^A),\theta^A) = u(c^B(\theta^A)) - h(z^B(\theta^A),\theta^A) - \frac{\psi}{p(\theta^A)}, \tag{4.64}$$

$$u'(z(\theta^A)) = h_z(z(\theta^A),\theta^A), \text{ and} \tag{4.65}$$

$$(1-r)u'(c^B(\theta^A)) = h_z(z(\theta^A),\theta^A). \tag{4.66}$$

Optimal Benefit Offset: Welfare is given by

$$\begin{aligned} W =& u(w-\tau) + \int_0^{\theta^A} u(z(\theta)) - h(z(\theta),\theta) dF(\theta) + \int_{\theta^A}^{\infty} p(\theta)[u(c^B(\theta)) - h(z^B(\theta),\theta) - \psi] dF(\theta) \\ &+ \int_{\theta^A}^{\infty} [1-p(\theta)][u(z(\theta)) - h(z(\theta),\theta) - \psi] dF(\theta). \end{aligned} \tag{4.67}$$

The government budget constraint is given by

$$\tau = \int_{\theta^A}^{\infty} p(\theta)(b - ry(\theta)) dF(\theta), \tag{4.68}$$

where y is defined as income above SGA, i.e.

$$y(\theta) = \begin{cases} z^B(\theta) - SGA, & \text{if } z^B(\theta) \geq SGA \\ 0, & \text{if } z^B(\theta) < SGA. \end{cases} \tag{4.69}$$

The welfare effect of a marginal change in the benefit offset rate r is

$$\frac{\partial W}{\partial r} = -\frac{\partial \tau}{\partial r} u'(w-\tau) - \int_{\theta^A}^{\infty} p(\theta) u'(c^B(\theta)) y(\theta) dF(\theta), \tag{4.70}$$

where

$$\frac{\partial \tau}{\partial r} = \underbrace{-\frac{\partial \theta^A}{\partial r} f(\theta^A) p(\theta^A)}_{\text{entry effect}} \left[b - ry(\theta^A)\right] - r \int_{\theta^A}^{\infty} p(\theta) \underbrace{\frac{\partial y(\theta)}{\partial r}}_{\text{labor supply effect}} dF(\theta)$$
$$\underbrace{- \int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta).}_{\text{mechanical costs}} \tag{4.71}$$

This is equivalent to the standard case. In fact, the only difference to the standard model is the determination of the marginal applicant θ^A. We can, however, still show the equivalence of $\frac{\partial \theta^A}{\partial r} = -\frac{\partial \theta^A}{\partial b} y(\theta^A) = -\frac{\partial \theta^A}{\partial SGA} \frac{y(\theta^A)}{r}$ using equations (4.64)–(4.66), as

$$\frac{\partial \theta^A}{\partial b} = -\frac{u'(c^B)}{h_\theta(z, \theta^A) - h_\theta(z^B, \theta^A) + \psi \frac{p'(\theta^A)}{p(\theta^A)^2}}, \tag{4.72}$$

$$\frac{\partial \theta^A}{\partial r} = \frac{u'(c^B) y(\theta^A)}{h_\theta(z, \theta^A) - h_\theta(z^B, \theta^A) + \psi \frac{p'(\theta^A)}{p(\theta^A)^2}}, \text{ and} \tag{4.73}$$

$$\frac{\partial \theta^A}{\partial SGA} = -\frac{u'(c^B) r}{h_\theta(z, \theta^A) - h_\theta(z^B, \theta^A) + \psi \frac{p'(\theta^A)}{p(\theta^A)^2}}. \tag{4.74}$$

Hence, we also arrive at

$$\frac{E[y(\theta) \frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)} | DI]}{E[y(\theta)|DI]} \geq -\varepsilon + \mu \left(\frac{b - ry(\theta^A)}{b}\right) \frac{y(\theta^A)}{E[y(\theta)|DI]}, \tag{4.75}$$

where μ is the benefit take-up elasticity with respect to b

$$\mu = \frac{\partial \int_{\theta^A}^{\infty} p(\theta) dF(\theta)}{\partial b} \frac{b}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)} = -\frac{\partial \theta^A}{\partial b} f(\theta^A) p(\theta^A) \frac{b}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)}. \tag{4.76}$$

Moving from Cash Cliff to Benefit Offset: All calculations from the main part of the paper still apply.

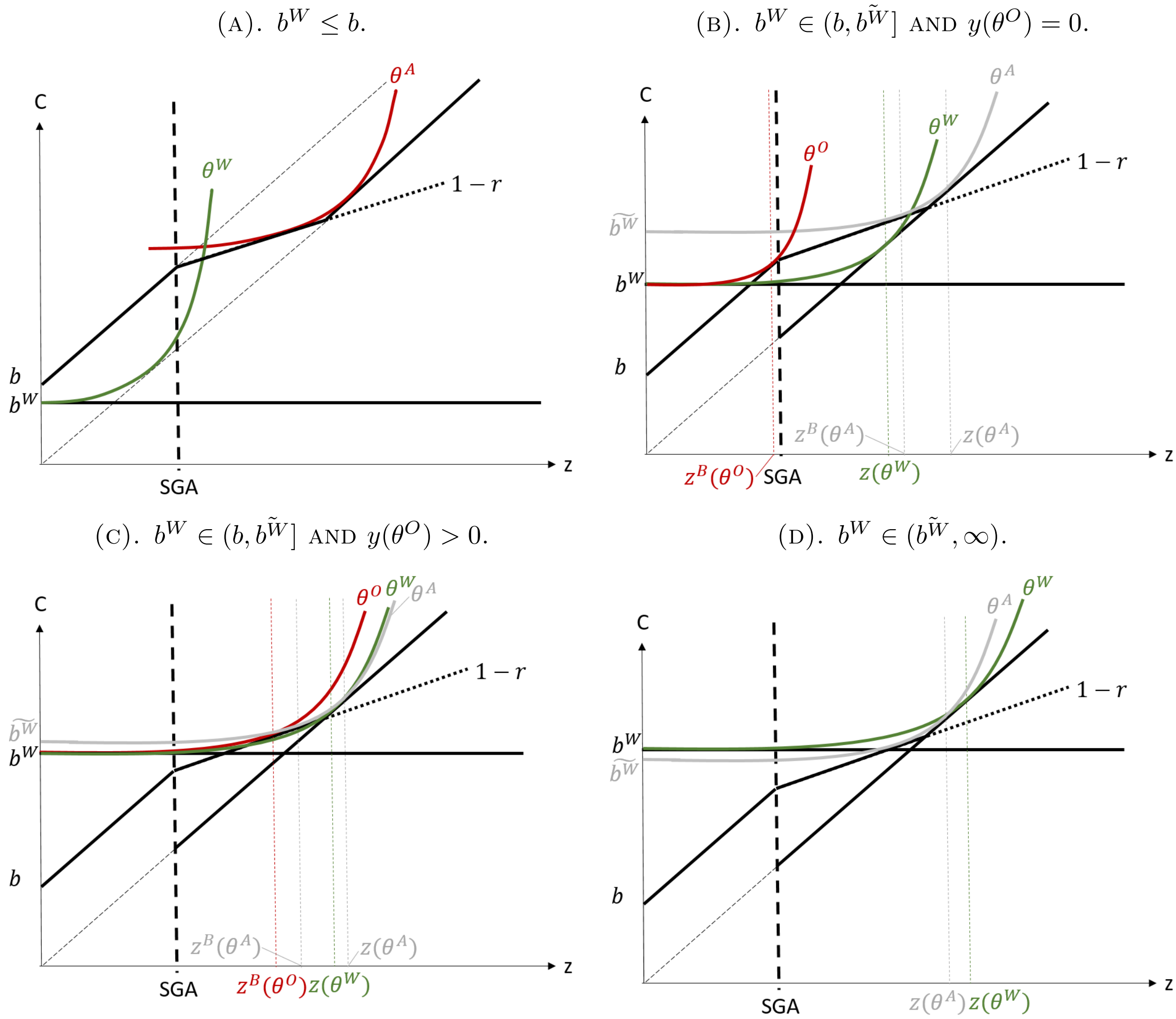
Benefit Substitution

In this subsection, we assume that all individuals have access to an unconditional welfare program (W) apart from DI. Everyone receiving benefits b^W is not allowed to supply any labor.

Optimal Benefit Offset: There are three possible scenarios for this unconditional welfare program to interact with DI depicted in Figure 4A.1: (1) the unconditional benefit paid is low $b^W \leq b$ (panel 4A.1a), (2) the unconditional benefit is intermediate $b^W \in (b, b^{\tilde{W}}]$ (panels 4A.1b and 4A.1c), and (3) the unconditional benefit is very high $b^W > b^{\tilde{W}}$ (panel 4A.1d). $b^{\tilde{W}}$ is the level of unconditional income that would set the marginal applicant

θ^A indifferent between working, applying to DI, and dropping out of the labor force to receive $\tilde{b^W}$ and is given by $u(\tilde{b^W}) = u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A) = u(z(\theta^A)) - h(z(\theta^A), \theta^A)$. In scenario (2), there are again two possible cases. Either the agent indifferent between W and DI with disutility of work θ^O supplies less labor than SGA/exactly SGA ($y(\theta^O) = 0$, panel 4A.1b) or she supplies more ($y(\theta^O) > 0$, panel 4A.1c). The scenarios and their implications for the model will be discussed in greater detail below.

Figure 4A.1. Benefit substitution scenarios.



Note: Panel 4A.1a corresponds to scenario 1, panels 4A.1b and 4A.1c correspond to scenario 2, and panel 4A.1d corresponds to scenario 3.

Scenario 1 $b^W \leq b$:

First, let us assume that $b^W \leq b$. This is the empirically most relevant case. With $b^W \leq b$, individuals that have the most severe disability (high θ) have an incentive to apply for disability insurance instead of not applying to DI and receiving the benefits of W. Phrased differently, if we assume that $b < b^W$the policy maker could increase b up to b^W without changing individuals' behavior.

Every individual with $\theta \geq \theta^W$ chooses to receive unconditional benefits b^W instead of working, where θ^W is determined by

$$u(b^W) = u(z(\theta^W)) - h(z(\theta^W), \theta^W). \tag{4.77}$$

Everything else remains as in the baseline model. By concavity of the utility function, we further know that everyone that does not supply labor, i.e. $\theta \geq \theta^W$, applies to DI. This means that $\theta^A \leq \tilde{\theta} \leq \theta^W$, where

$$u(b) = u(z(\tilde{\theta})) - h(z(\tilde{\theta}), \tilde{\theta}) \tag{4.78}$$

$$u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A) = u(z(\theta^A)) - h(z(\theta^A), \theta^A). \tag{4.79}$$

Consequently, welfare is given by

$$\begin{aligned} W^{W1} =& u(w-\tau) + \int_0^{\theta^A} u(z(\theta)) - h(z(\theta), \theta) dF(\theta) \\ &+ \int_{\theta^A}^{\infty} p(\theta)[u(c^B(\theta)) - h(z^B(\theta), \theta) dF(\theta) \\ &+ \int_{\theta^A}^{\theta^W} (1-p(\theta))[u(z(\theta)) - h(z(\theta), \theta)] dF(\theta) \\ &+ \int_{\theta^W}^{\infty} (1-p(\theta)) u(b^W) dF(\theta). \end{aligned} \tag{4.80}$$

The government budget constraint is equal to

$$\tau = \int_{\theta^A}^{\infty} p(\theta)[b - ry(\theta)] dF(\theta) + \int_{\theta^W}^{\infty} (1-p(\theta)) b^W dF(\theta). \tag{4.81}$$

The partial derivative of welfare with respect to the offset r is

$$\frac{\partial W^{W1}}{\partial r} = -u'(w-\tau)\frac{\partial \tau}{\partial r} - \int_{\theta^A}^{\infty} p(\theta) u'(c^B(\theta)) y(\theta) dF(\theta) \tag{4.82}$$

with

$$\frac{\partial \tau}{\partial r} = -\int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta) - \int_{\theta^A}^{\infty} p(\theta) r \frac{\partial y(\theta)}{\partial r} dF(\theta) + \frac{\partial \theta^A}{\partial r} p(\theta^A) f(\theta^A)(ry(\theta) - b). \tag{4.83}$$

Hence, the optimality conditions are the same as in the baseline model. The only difference is that apart from b, SGA, and r the policy maker has to choose the optimal level of unconditional welfare benefits b^W. This is, however, orthogonal to the optimal benefit offset program.

Scenario 2 $b^W \in (b, \tilde{b^W}]$:

Second, let us assume that $b^W \in (b, b^{\tilde{W}}]$. In this scenario, we have to consider three marginal agents. The first agent with θ^A is indifferent between being applying to DI with labor supply $z^B(\theta^A)$ and supplying $z(\theta^A)$ without assistance. The second agent with θ^O is indifferent between receiving unconditional welfare and being on DI with labor supply $z^B(\theta^O)$. The third agent with θ^W is indifferent between receiving unconditional welfare and supplying $z(\theta^W)$ without assistance. They are determined by the following equations

$$u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A) = u(z(\theta^A)) - h(z(\theta^A), \theta^A), \tag{4.84}$$

$$u(c^B(\theta^O)) - h(z^B(\theta^O), \theta^O) = u(b^W), \text{ and} \tag{4.85}$$

$$u(z(\theta^W)) - h(z(\theta^W), \theta^W) = u(b^W). \tag{4.86}$$

By $b^W \leq b^{\tilde{W}}$ and the definition of $b^{\tilde{W}}$, it follows that $u(b^W) \leq u(b^{\tilde{W}}) = u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A)$. Together with equations (4.84)–(4.86), we get $\theta^W \geq \theta^A$ and $\theta^O \geq \theta^A$. Hence, both θ^W- and θ^O-individuals would prefer applying to DI rather than working. Hence, we know that

$$\begin{aligned} u(z(\theta^O)) - h(z(\theta^O), \theta^O) &\leq u(c^B(\theta^O)) - h(z^B(\theta^O), \theta^O) = u(b^W) \\ &= u(z(\theta^W)) - h(z(\theta^W), \theta^W) \\ &\leq u(c^B(\theta^W)) - h(z^B(\theta^W), \theta^W), \end{aligned} \tag{4.87}$$

which implies that $\theta^O \geq \theta^W \geq \theta^A$. We can distinguish between four types of agents: (1) agents that drop out of the labor force to receive unconditional benefits $\theta \in [\theta^O, \infty)$, (2) agents that apply to DI and drop out of the labor force if they are rejected $\theta \in [\theta^W, \theta^O)$, (3) agents that apply to DI and work without assistance if rejected $\theta \in [\theta^A, \theta^W)$, and (4) agents that do not apply to DI and work without assistance $\theta \in [0, \theta^A)$. Welfare is given by

$$\begin{aligned} W^{W2} =& u(w-\tau) + \int_0^{\theta^A} u(z(\theta)) - h(z(\theta), \theta) dF(\theta) \\ &+ \int_{\theta^A}^{\theta^O} p(\theta)[u(c^B(\theta)) - h(z^B(\theta), \theta)] dF(\theta) \\ &+ \int_{\theta^A}^{\theta^W} (1-p(\theta))[u(z(\theta)) - h(z(\theta), \theta)] dF(\theta) + \int_{\theta^W}^{\theta^O} (1-p(\theta)) u(b^W) dF(\theta) \\ &+ \int_{\theta^O}^{\infty} u(b^W) dF(\theta). \end{aligned} \tag{4.88}$$

The government budget constraint is given by

$$\tau = \int_{\theta^A}^{\theta^O} p(\theta)[b - ry(\theta)] dF(\theta) + \int_{\theta^W}^{\theta^O} (1-p(\theta)) b^W dF(\theta) + \int_{\theta^O}^{\infty} b^W dF(\theta). \tag{4.89}$$

A marginal change in the offset rate r causes welfare to change according to

$$\frac{\partial W^{W2}}{\partial r} = -u'(w-\tau)\frac{\partial \tau}{\partial r} - \int_{\theta^A}^{\theta^O} p(\theta)u'(c^B(\theta))y(\theta)dF(\theta) \tag{4.90}$$

with

$$\begin{aligned}\frac{\partial \tau}{\partial r} =& -\frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A)[b-ry(\theta^A)] - r\int_{\theta^A}^{\theta^O} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta) \\ &- \int_{\theta^A}^{\theta^O} p(\theta)y(\theta)dF(\theta) + \underbrace{\frac{\partial \theta^O}{\partial r}p(\theta^O)f(\theta^O)[b-ry(\theta^O)-b^W]}_{\text{program substitution effect}}.\end{aligned} \tag{4.91}$$

Note that the *program substitution effect* is zero if $\frac{\partial \theta^O}{\partial r} = 0$. This condition holds if $y(\theta^O) = 0$ which is equivalent to $(1-r)u'(b+SGA) \leq h_z(SGA, \theta^O)$. Otherwise, the program substitution effect is negative. A smaller benefit offset makes DI more attractive as compared to the unconditional welfare program inducing DI entry and W exit. As the costs of W are higher than those of DI, taxes can be reduced to balance the government budget.

We can rewrite the optimality condition as

$$\begin{aligned}\frac{\partial \tilde{W}^{W2}}{\partial r} =& \frac{\partial W^{W2}/\partial r}{u'(w-\tau)} = \frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A)[b-ry(\theta^A)] + r\int_{\theta^A}^{\theta^O} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta) \\ &- \int_{\theta^A}^{\theta^O} p(\theta)y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}dF(\theta) \\ &- \frac{\partial \theta^O}{\partial r}p(\theta^O)f(\theta^O)[b-ry(\theta^O)-b^W] \\ =& [\frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A) - \frac{\partial \theta^O}{\partial r}p(\theta^O)f(\theta^O)][b-ry(\theta^A)] \\ &- \frac{\partial \theta^O}{\partial r}p(\theta^O)f(\theta^O)[ry(\theta^A)-ry(\theta^O)-b^W] \\ &+ r\int_{\theta^A}^{\theta^O} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta) - \int_{\theta^A}^{\theta^O} p(\theta)y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}dF(\theta).\end{aligned} \tag{4.92}$$

Hence, welfare decreases in the offset rate r if

$$\begin{aligned}\frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y(\theta)|DI]} \geq& -\varepsilon - \nu\frac{b-ry(\theta^A)}{E[y(\theta)|DI]} \\ &+ \kappa\frac{ry(\theta^A)-ry(\theta^O)-b^W}{E[y(\theta)|DI]}\frac{P(DI)}{P(W)},\end{aligned} \tag{4.93}$$

where ε is the earnings elasticity of DI recipients

$$\varepsilon := \int_{\theta^A}^{\theta^O} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta)\frac{r}{\int_{\theta^A}^{\theta^O} p(\theta)y(\theta)dF(\theta)}, \tag{4.94}$$

ν is the DI take-up semi-elasticity with respect to r

$$\begin{aligned}\nu :=& \frac{\partial[\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)]}{\partial r}\frac{1}{\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)}\\ =&[\frac{\partial\theta^O}{\partial r}p(\theta^O)f(\theta^O) - \frac{\partial\theta^A}{\partial r}p(\theta^A)f(\theta^A)]\frac{1}{\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)},\end{aligned} \tag{4.95}$$

and κ is the W take-up semi-elasticity (program substitution) with respect to r

$$\begin{aligned}\kappa :=& \frac{\partial[\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta) + \int_{\theta^O}^{\infty} dF(\theta)]}{\partial r}\frac{1}{\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta) + \int_{\theta^O}^{\infty} dF(\theta)}\\ =& -\frac{\frac{\partial\theta^O}{\partial r}f(\theta^O)p(\theta^O)}{\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta) + \int_{\theta^O}^{\infty} dF(\theta)},\end{aligned} \tag{4.96}$$

and

$$P(DI) := \int_{\theta^A}^{\theta^O} p(\theta)dF(\theta), \tag{4.97}$$

and

$$P(W) := \int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta) + \int_{\theta^O}^{\infty} dF(\theta). \tag{4.98}$$

It can be shown that $\frac{\partial\theta^A}{\partial r} = -\frac{\partial\theta^A}{\partial b}y(\theta^A)$ and $\frac{\partial\theta^O}{\partial r} = -\frac{\partial\theta^O}{\partial b}y(\theta^O)$, allowing to rewrite condition 4.93 as

$$\begin{aligned}\frac{E[y(\theta)\frac{u'(c^B(\theta))-u'(w-\tau)}{u'(w-\tau)}|DI]}{E[y(\theta)|DI]} \geq& -\varepsilon + \mu\frac{b - ry(\theta^A)}{b}\frac{y(\theta^A)}{E[y(\theta)|DI]}\\ &- \omega\frac{y(\theta^O)[b - ry(\theta^O) - b^W] - y(\theta^A)[b - ry(\theta^A)]}{bE[y(\theta)|DI]}\frac{P(DI)}{P(W)},\end{aligned} \tag{4.99}$$

where μ is the DI take-up elasticity with respect to b

$$\begin{aligned}\mu :=& \frac{\partial[\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)]}{\partial b}\frac{b}{\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)}\\ =&[\frac{\partial\theta^O}{\partial b}p(\theta^O)f(\theta^O) - \frac{\partial\theta^A}{\partial b}p(\theta^A)f(\theta^A)]\frac{b}{\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)}\end{aligned} \tag{4.100}$$

and ω is the W take-up elasticity (program substitution) with respect to b

$$\begin{aligned}\omega :=& \frac{\partial[\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta)+\int_{\theta^O}^{\infty}dF(\theta)]}{\partial b}\frac{b}{\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta)+\int_{\theta^O}^{\infty}dF(\theta)}\\ =& -b\frac{\frac{\partial\theta^O}{\partial b}f(\theta^O)p(\theta^O)}{\int_{\theta^W}^{\theta^O}(1-p(\theta))dF(\theta)+\int_{\theta^O}^{\infty}dF(\theta)}. \end{aligned} \tag{4.101}$$

Scenario 3 $b^W > b^{\tilde{W}}$:

Third, let us assume that $b^W > b^{\tilde{W}}$. Consequently, we have $u(b^W) > u(b^{\tilde{W}}) = u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A)$. This means that even the agent that is indifferent between applying to disability insurance and working prefers dropping out of the labor force over DI. In this scenario, the benefit offset does not affect welfare. Phrased differently, if the government would want to induce DI entry the offset rate r would have to be very low. Welfare is given by

$$\begin{aligned}W^{W3} =& u(w-\tau)+\int_0^{\theta^W}u(z(\theta))-h(z(\theta),\theta)dF(\theta)\\ &+\int_{\theta^W}^{\infty}u(b^W)dF(\theta). \end{aligned} \tag{4.102}$$

The government budget constraint is given by

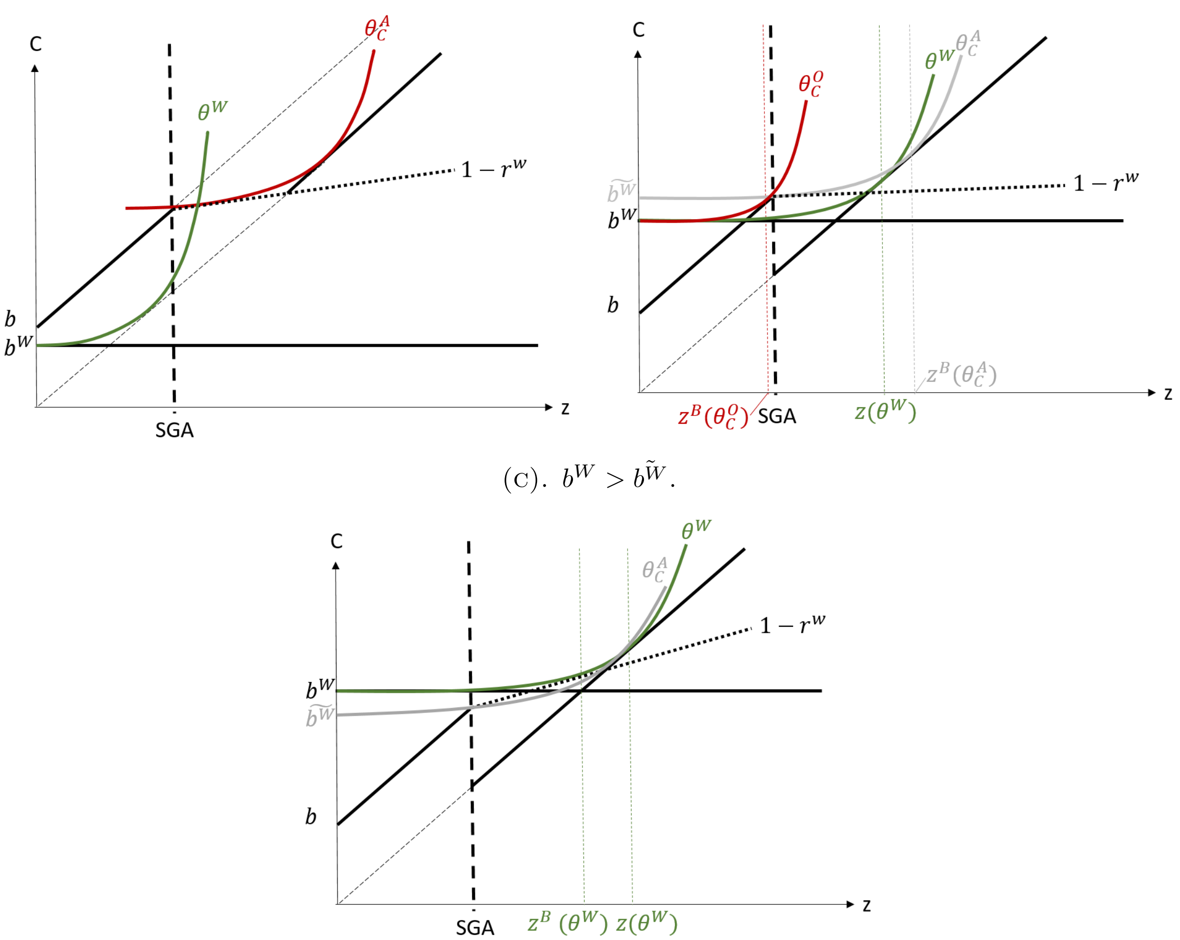
$$\tau = \int_{\theta^W}^{\infty} b^W dF(\theta). \tag{4.103}$$

Consequently, it is not possible to calculate the optimal offset rate in this scenario. The limit case of this scenario would be to decrease r until we arrive at scenario 2.

Moving from Cash Cliff to Benefit Offset: Again there are three possible scenarios for the unconditional welfare program to interact with DI moving from a cash cliff system to a benefit offset system. The three scenarios are depicted in Figure 4A.2. Note the differential definition of $b^{\tilde{W}}$. It is the level of unconditional income that would set the marginal applicant under the cash cliff system θ_C^A indifferent between working, applying to DI, and dropping out of the labor force to receive $b^{\tilde{W}}$ and is given by $u(b^{\tilde{W}}) = u(c^B(\theta_C^A)) - h(SGA, \theta_C^A) = u(z(\theta_C^A)) - h(z(\theta_C^A), \theta_C^A)$. Scenario 1 in this section corresponds to scenario 1 in the Optimal Benefit Offset section, scenario 2 corresponds to scenario 2 with $y(\theta^O) = 0$ in the Optimal Benefit Offset section, and scenario 3 corresponds to scenario 2 with $y(\theta^O) > 0$ and scenario 3 in the Optimal Benefit Offset section. θ^O still denotes the level of disutility of work of the individual that is indifferent between applying to DI and W. Below, the scenarios are described in detail.

Figure 4A.2. Benefit substitution—cash cliff to benefit offset scenarios.

(a). $b^W \leq b$. (b). $b^W \in (b, b^{\tilde{W}}]$. (c). $b^W > b^{\tilde{W}}$.



Note: Panel 4A.2a corresponds to scenario 1, panel 4A.2b corresponds to scenario 2, and panel 4A.2c corresponds to scenario 3. r^w is the maximum offset rate leaving the cash cliff and the benefit offset system equivalent. In scenarios 1 and 2, it is determined by $1 - r^w = \frac{h_z(SGA, \theta_C^A)}{u'(b+SGA)}$. In scenario 3, it is determined by $u(c^B(\theta^W)) - h(z^B(\theta^W), \theta^W) = u(b^W)$ with $c^B(\theta^W) = b + SGA + (1 - r^w)(z^B(\theta^W) - SGA)$.

Scenario 1 $b^W \leq b$:

From the results in the previous section, it follows that moving from a cash cliff to a benefit offset system in this scenario is analogous to the baseline case without the unconditional welfare program W.

Scenario 2 $b^W \in (b, b^{\tilde{W}}]$:

As in the previous section, we have three marginal agents to consider. The agent with θ_C^A is indifferent between being applying to DI with labor supply SGA and supplying $z(\theta_C^A)$ without assistance. The agent with θ^O is indifferent between receiving unconditional welfare and being on DI with labor supply $z^C(\theta^O)$. The last agent with θ^W is indifferent between receiving unconditional welfare and supplying $z(\theta^W)$ without assistance. They are determined by the following equations

$$u(c^C(\theta^A_C)) - h(SGA, \theta^A_C) = u(z(\theta^A_C)) - h(z(\theta^A_C), \theta^A_C), \tag{4.104}$$

$$u(c^C(\theta^O)) - h(z^C(\theta^O), \theta^O) = u(b^W), \text{ and} \tag{4.105}$$

$$u(z(\theta^W)) - h(z(\theta^W), \theta^W) = u(b^W). \tag{4.106}$$

with

$$c^C(\theta) = \begin{cases} b + z^C(\theta), & \text{if } z^C(\theta) \le SGA, \\ z^C(\theta), & \text{if } z^B(\theta) > SGA. \end{cases} \tag{4.107}$$

By $b^W \le b^{\tilde{W}}$ and the definition of $b^{\tilde{W}}$, it follows that $u(b^W) \le u(b^{\tilde{W}}) = u(c^C(\theta^A_C)) - h(SGA, \theta^A_C)$. Together with equations (4.104)–(4.106), we get $\theta^W \ge \theta^A_C$ and $\theta^O \ge \theta^A_C$. Hence, both θ^W- and θ^O-individuals would prefer applying to DI rather than working. Hence, we know that

$$\begin{aligned} u(z(\theta^O)) - h(z(\theta^O), \theta^O) &\le u(c^C(\theta^O)) - h(z^C(\theta^O), \theta^O) = u(b^W) \\ &= u(z(\theta^W)) - h(z(\theta^W), \theta^W) \\ &\le u(c^C(\theta^W)) - h(z^C(\theta^W), \theta^W), \end{aligned} \tag{4.108}$$

which implies that $\theta^O \ge \theta^W \ge \theta^A$. We can distinguish between four types of agents: (1) agents that drop out of the labor force to receive unconditional benefits $\theta \in [\theta^O, \infty)$, (2) agents that apply to DI and drop out of the labor force if they are rejected $\theta \in [\theta^W, \theta^O)$, (3) agents that apply to DI and work without assistance if rejected $\theta \in [\theta^A, \theta^W)$, and (4) agents that do not apply to DI and work without assistance $\theta \in [0, \theta^A)$. Welfare under the cash cliff system is given by

$$\begin{aligned} W^{CW2} =& u(w - \tau^C) + \int_0^{\theta^A_C} u(z(\theta)) - h(z(\theta), \theta) dF(\theta) \\ &+ \int_{\theta^A_C}^{\theta^O} p(\theta)[u(c^C(\theta)) - h(z^C(\theta), \theta)] dF(\theta) \\ &+ \int_{\theta^A_C}^{\theta^W} (1 - p(\theta))[u(z(\theta)) - h(z(\theta), \theta)] dF(\theta) + \int_{\theta^W}^{\theta^O} (1 - p(\theta)) u(b^W) dF(\theta) \\ &+ \int_{\theta^O}^{\infty} u(b^W) dF(\theta). \end{aligned} \tag{4.109}$$

We now study the effect of moving from a cash cliff to a benefit offset program. To do so, we analyze the opposite change, i.e. moving from a benefit offset with work incentives $r < r^w$ closer to r^w being equivalent to a cash cliff scheme. This way, we can start with $r = r^w - \epsilon$ with $\epsilon > 0$ and let $\epsilon \to 0$. For all $\epsilon > 0$, we have an interior marginal applicant.

Note that for $r = r^w$, $y(\theta) = 0 \,\forall\, \theta \in [\theta_C^A, \theta^O)$. Further, we know that $\lim_{r\to r^w} \theta^A = \theta_C^A$ and thus $\lim_{r\to r^w} y(\theta^A) = y(\theta_C^A)$. Let us now consider the limit case of equation 4.100. First, let us calculate the limit of the LHS of equation 4.100. We know that

$$\frac{u'(c^B(\theta^A)) - u'(w-\tau)}{u'(w-\tau)} E[y(\theta)|DI] \le E[y(\theta)\frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)}|DI] \tag{4.110}$$
$$\le \frac{u'(b+SGA) - u'(w-\tau)}{u'(w-\tau)} E[y(\theta)|DI].$$

Hence, the limit of the LHS is given by

$$\lim_{r\to r^w} E[y(\theta)\frac{u'(c^B(\theta)) - u'(w-\tau)}{u'(w-\tau)}|DI] = \frac{u'(b+SGA) - u'(w-\tau)}{u'(w-\tau)}. \tag{4.111}$$

Because $\frac{y(\theta^A)}{E[y(\theta)|DI]} \ge 1$ and $y(\theta^O) = 0$, the limit of the components on the RHS are given by

$$\lim_{r\to r^w} \frac{b - ry(\theta^A)}{b} = 1, \tag{4.112}$$
$$\lim_{r\to r^w} \frac{y(\theta^A)}{E[y(\theta)|DI]} = 1, \text{ and} \tag{4.113}$$
$$\lim_{r\to r^w} \frac{\int_{\theta^A}^{\theta^O} p(\theta)dF(\theta)}{\int_{\theta^O}^{\infty} dF(\theta) + \int_{\theta^W}^{\theta^O} 1 - p(\theta)dF(\theta)} = \frac{\int_{\theta_C^A}^{\theta_C^O} p(\theta)dF(\theta)}{\int_{\theta_C^O}^{\infty} dF(\theta) + \int_{\theta^W}^{\theta_C^O} 1 - p(\theta)dF(\theta)}$$
$$= \frac{P(DI)^C}{P(W)^C}. \tag{4.114}$$

Hence, the limit of the RHS is given by

$$\lim_{r\to r^w} -\varepsilon + \mu\frac{b - ry(\theta^A)}{b}\frac{y(\theta^A)}{E[y(\theta)|DI]} - \omega\frac{y(\theta^O)[b - ry(\theta^O) - b^W] - y(\theta^A)[b - ry(\theta^A)]}{bE[y(\theta)|DI]}\frac{P(DI)}{P(W)}$$
$$= -\varepsilon + \mu - \omega\frac{P(DI)^C}{P(W)^C}. \tag{4.115}$$

The condition for $\frac{\partial W^{W2}}{\partial r} \le 0$ becomes

$$\frac{u'(b+SGA) - u'(w-\tau)}{u'(w-\tau)} \ge -\varepsilon + \mu - \omega\frac{P(DI)^C}{P(W)^C}. \tag{4.116}$$

The last term might seem counter-intuitive at first. Panel 4A.2b nicely shows that the θ^O will not react to the introduction of the benefit offset system. The term's origin lies in the definition of μ, which is the DI benefit take-up elasticity with respect to b. It comprises both the reaction of the lower marginal applicant to DI θ^A and the upper marginal applicant to DI θ^O. As θ^O increases in b (more individuals prefer DI over W), we have to correct for this effect. This correction is captured by the new term $\omega\frac{P(DI)^C}{P(W)^C}$, which is the unconditional welfare benefit take-up elasticity with respect to b weighted by the fraction of individuals on DI relative to the fraction of individuals on unconditional welfare W.

Scenario 3 $b^W > \tilde{b^W}$*:*

This is not an empirically relevant case as no individual will apply to DI. Thus, the hypothetical marginal applicant to the cash cliff system no longer is the marginal applicant under the maximum benefit offset system (b, r^w, SGA). Instead the marginal W receiver has to be set indifferent between DI, W, and working to arrive at the maximum offset r^w. The maximum offset is defined by $u(c^B(\theta^W)) - h(z^B(\theta^W), \theta^W) = u(b^W)$ with $c^B(\theta^W) = b + SGA + (1 - r^w)(z^B(\theta^W) - SGA)$. Rather than introducing a benefit offset scheme to the DI program in that scenario, the government could instead introduce a benefit offset or earnings exempt to the unconditional welfare program to improve labor incentives in this economy.

Frictions: Adjustment Costs

This extension is still work in progress. In general, one can always think of adjustment costs when changing labor supply as a particular form of heterogeneity as extensively discussed in Section 4B. There might be a distribution across adjustment costs in the population with some individuals that need strong incentives to change labor supply and others that have adjustment costs close to zero—the latter would correspond to individuals treated in the baseline model. Consequently, the reaction caused by changes to the DI program would just be focused in one particular part of the population. The parameters one would have to estimate, however, would still be the same. Other possibilities to incorporate adjustment costs when changing labor supply are presented in Gelber et al. (2017) or Kleven and Waseem (2013). They require non-marginal policy changes, which we did not yet include into the model.

Other Sources of Heterogeneity

Setup: Let us assume that there is some other source of heterogeneity affecting an individual's choice of labor supply apart from the level of disability θ. Let us call this heterogeneity $a \in (-\infty, \infty)$ and assume that there is some joint smooth distribution of θ and a denoted by $G(\theta, a)$. Let us assume that what we denoted before by $F(\theta)$ is actually the conditional distribution of θ given a corresponding to $F(\theta|a)$. Let us denote the unconditional distribution of a by $H(a)$. Hence, the choices of optimal labor supply without DI benefits and with DI benefits are given by

$$z(\theta, a) := \arg\max_{z \geq 0} u(z) - h(z, \theta, a), \tag{4.117}$$

$$z^B(\theta, a) := \arg\max_{z^B \geq 0} u(c^B(\theta, a)) - h(z^B, \theta, a), \tag{4.118}$$

with

$$c^B(\theta, a) := \begin{cases} b + z^B(\theta, a), & \text{if } z^B(\theta, a) \leq SGA, \\ b + SGA + (1-r)y(\theta, a), & \text{if } z^B(\theta, a) > SGA, \end{cases} \tag{4.119}$$

and

$$y(\theta, a) := \begin{cases} 0, & \text{if } z^B(\theta, a) \leq SGA, \\ z^B(\theta, a) - SGA, & \text{if } z^B(\theta, a) > SGA. \end{cases} \tag{4.120}$$

Moreover, let us assume that the wage rate in the first period also potentially depends on the heterogeneity parameter a such that utility in the first period is given by $u(w(a)-\tau)$. There is a marginal DI applicant $\theta^A(a)$ for every value of the heterogeneity parameter a given by

$$\begin{aligned} &u[c^B(\theta^A(a), a)] - h[z^B(\theta^A(a), a), \theta^A(a), a] \\ &= u[z(\theta^A(a), a)] - h[z(\theta^A(a), a), \theta^A(a), a]. \end{aligned} \tag{4.121}$$

Welfare is given by

$$\begin{aligned} W = \int_{-\infty}^{\infty} &\{u(w(a) - \tau) + \int_0^{\theta^A(a)} u(z(\theta, a)) - h(z(\theta, a), \theta, a) dF(\theta|a) \\ &+ \int_{\theta^A(a)}^{\infty} p(\theta, a)[u(c^B(\theta, a)) - h(z^B(\theta, a), \theta, a) dF(\theta|a) \\ &+ \int_{\theta^A(a)}^{\infty} [1 - p(\theta, a)][u(z(\theta, a)) - h(z(\theta, a), \theta, a)] dF(\theta|a)\} dH(a). \end{aligned} \tag{4.122}$$

The government budget constraint is given by

$$\tau = \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a)[b - ry(\theta, a)] dF(\theta|a)\} dH(a). \tag{4.123}$$

Optimal Benefit Offset: A marginal change in the offset rate has a welfare effect of

$$\frac{\partial W}{\partial r} = \int_{-\infty}^{\infty} \{-\frac{\partial \tau}{\partial r} u'(w(a) - \tau) - \int_{\theta^A(a)}^{\infty} p(\theta, a) u'(c^B(\theta, a)) y(\theta, a) dF(\theta|a)\} dH(a) \tag{4.124}$$

with

$$\frac{\partial \tau}{\partial r} = \int_{-\infty}^{\infty} \{-\frac{\partial \theta^A(a)}{\partial r} p(\theta^A(a), a) f(\theta^A(a)|a)[b - ry(\theta^A(a), a)] \\ - \int_{\theta^A(a)}^{\infty} rp(\theta, a) \frac{\partial y(\theta, a)}{\partial r} dF(\theta|a) - \int_{\theta^A(a)}^{\infty} p(\theta, a) y(\theta, a) dF(\theta|a)\} dH(a). \tag{4.125}$$

Note that $\partial\tau/\partial r$ and $E[u'(a) - \tau] := \int_{-\infty}^{\infty} u'(w(a) - \tau) dH(a)$ are independent of a. Combining everything, we get

$$\frac{\partial W}{\partial r} = - \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) u'(c^B(\theta, a)) y(\theta, a) dF(\theta|a)\} dH(a) \\ + \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) E[u'(a) - \tau] y(\theta, a) dF(\theta|a)\} dH(a) \\ + E[u'(a) - \tau] \int_{-\infty}^{\infty} \{\frac{\partial \theta^A(a)}{\partial r} p(\theta^A(a), a) f(\theta^A(a)|a)[b - ry(\theta^A(a), a)] \\ + \int_{\theta^A(a)}^{\infty} rp(\theta, a) \frac{\partial y(\theta, a)}{\partial r} dF(\theta|a)\} dH(a). \tag{4.126}$$

Dividing by $E[u'(a) - \tau]$ on both sides yields

$$\frac{\partial \tilde{W}}{\partial r} = - \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} \frac{u'(c^B(\theta, a)) - E[u'(w(a) - \tau)]}{E[u'(w(a) - \tau)]} p(\theta, a) y(\theta, a) dF(\theta|a)\} dH(a) \\ + \int_{-\infty}^{\infty} \{\frac{\partial \theta^A(a)}{\partial r} p(\theta^A(a), a) f(\theta^A(a)|a) b\} dH(a) \\ - \int_{-\infty}^{\infty} \{\frac{\partial \theta^A(a)}{\partial r} p(\theta^A(a), a) f(\theta^A(a)|a) ry(\theta^A(a), a)\} dH(a) \\ + \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} rp(\theta, a) \frac{\partial y(\theta, a)}{\partial r} dF(\theta|a)\} dH(a). \tag{4.127}$$

Let us define the earnings elasticity by

$$\tilde{\varepsilon} := - \int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) \frac{\partial y(\theta, a)}{\partial r} dF(\theta|a)\} dH(a) \frac{r}{\int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) y(\theta, a) dF(\theta|a)\} dH(a)}, \tag{4.128}$$

the benefit take-up semi-elasticity with respect to r by

$$\tilde{\nu} := - \frac{\partial [\int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) dF(\theta|a)\} dH(a)]}{\partial r} \frac{1}{\int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) dF(\theta|a)\} dH(a)} \\ = \frac{\int_{-\infty}^{\infty} \{\frac{\partial \theta^A(a)}{\partial r} p(\theta^A(a), a) f(\theta^A(a)|a)\} dH(a)}{\int_{-\infty}^{\infty} \{\int_{\theta^A(a)}^{\infty} p(\theta, a) dF(\theta|a)\} dH(a)}, \tag{4.129}$$

the benefit take-up elasticity with respect to b $\tilde{\mu}$ by

$$\begin{aligned}\tilde{\mu} :&= \frac{\partial[\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)]}{\partial b}\frac{b}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)} \\ &= -\frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial b}p(\theta^A(a),a)f(\theta^A(a)|a)\}dH(a)}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)}, \end{aligned} \tag{4.130}$$

the expected excess labor supply of DI recipients beyond SGA by

$$E[E[y(\theta,a)|DI,a]] := \frac{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)y(\theta,a)dF(\theta|a)\}dH(a)}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)}, \tag{4.131}$$

and the consumption smoothing effect of changing work incentives

$$\begin{aligned}&E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]] \\ &:= \frac{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty}\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}p(\theta,a)y(\theta,a)dF(\theta|a)\}dH(a)}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)}.\end{aligned} \tag{4.132}$$

Dividing equation (4.127) by $\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)y(\theta,a)dF(\theta|a)\}dH(a)$ yields

$$\begin{aligned}\frac{\partial\bar{W}}{\partial r} =& -\frac{E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} \\ &-\tilde{\varepsilon}+\tilde{\nu}\frac{b}{E[E[y(\theta,a)|DI,a]]} \\ &-\frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial r}p(\theta^A(a),a)f(\theta^A(a)|a)ry(\theta^A(a),a)\}dH(a)}{E[E[y(\theta,a)|DI,a]]\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)}.\end{aligned} \tag{4.133}$$

Hence, a decrease in the offset rate increases welfare (i.e. $\frac{\partial W}{\partial r} \leq 0$) whenever

$$\begin{aligned}&\frac{E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} \geq -\tilde{\varepsilon}+\tilde{\nu}\frac{b}{E[E[y(\theta,a)|DI,a]]} \\ &-\frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial r}p(\theta^A(a),a)f(\theta^A(a)|a)ry(\theta^A(a),a)\}dH(a)}{E[E[y(\theta,a)|DI,a]]\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)}.\end{aligned} \tag{4.134}$$

Note that $\frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial r}p(\theta^A(a),a)f(\theta^A(a)|a)ry(\theta^A(a),a)\}dH(a)}{E[E[y(\theta,a)|DI,a]]\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty} p(\theta,a)dF(\theta|a)\}dH(a)} \in [\tilde{\nu}\frac{ry(\theta^A(a_{max}),a_{max})}{E[E[y(\theta,a)|DI,a]]}, \tilde{\nu}\frac{ry(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}]$, where a_{min} (a_{max}) is the level of a that yields the minimum (maximum) optimal excess labor supply beyond SGA of the marginal DI applicant. Consequently, we can define a sufficient and a necessary condition for $\frac{\partial W}{\partial r} \leq 0$, which are given by

$$\frac{E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} \geq \underbrace{-\tilde{\varepsilon}+\tilde{\nu}\frac{b-ry(\theta^A(a_{max}),a_{max})}{E[E[y(\theta,a)|DI,a]]}}_{\text{sufficient condition}} \tag{4.135}$$

$$\begin{aligned}
&\geq -\tilde{\varepsilon}+\tilde{\nu}\frac{b}{E[E[y(\theta,a)|a]]} \\
&\quad - \frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial r}p(\theta^A(a),a)f(\theta^A(a)|a)ry(\theta^A(a),a)\}dH(a)}{E[E[y(\theta,a)|DI,a]]\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty}p(\theta,a)dF(\theta|a)\}dH(a)} \\
&\geq \underbrace{-\tilde{\varepsilon}+\tilde{\nu}\frac{b-ry(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}}_{\text{necessary condition}} \\
&\geq -\tilde{\varepsilon}+\tilde{\nu}\frac{b}{E[E[y(\theta,a)|DI,a]]}.
\end{aligned}$$

It still holds that $\frac{\partial\theta^A(a)}{\partial r} = -y(\theta^A(a),a)\frac{\partial\theta^A(a)}{\partial b}$. Hence, we can rewrite the condition for $\frac{\partial W}{\partial r} \leq 0$ as

$$\begin{aligned}
&\frac{E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} \geq -\tilde{\varepsilon} \\
&- \frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial b}y(\theta^A(a),a)p(\theta^A(a),a)f(\theta^A(a)|a)[b-ry(\theta^A(a),a)]\}dH(a)}{E[E[y(\theta,a)|DI,a]]\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty}p(\theta,a)dF(\theta|a)\}dH(a)}.
\end{aligned} \tag{4.136}$$

We can bound the latter term on the RHS by

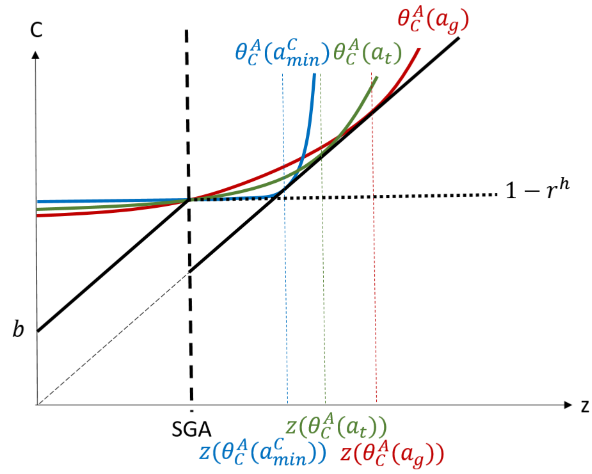
$$\begin{aligned}
&\tilde{\mu}\frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}\frac{b-ry(\theta^A(a_{max}),a_{max})}{b} \\
&\geq -\frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial b}y(\theta^A(a),a)p(\theta^A(a),a)f(\theta^A(a)|a)[b-ry(\theta^A(a),a)]\}dH(a)}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty}p(\theta,a)dF(\theta|a)\}dH(a)E[E[y(\theta,a)|a]]} \\
&\geq \tilde{\mu}\frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}\frac{b-ry(\theta^A(a_{max}),a_{max})}{b}.
\end{aligned} \tag{4.137}$$

Hence, we get the sufficient and the necessary condition for $\frac{\partial W}{\partial r} \leq 0$

$$\begin{aligned}
&\frac{E[E[\frac{u'(c^B(\theta,a))-E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} \\
&\underbrace{\geq -\tilde{\varepsilon} + \tilde{\mu}\frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}\frac{b - ry(\theta^A(a_{max}),a_{max})}{b}}_{\text{sufficient condition}} \\
&\geq -\tilde{\varepsilon} - \frac{\int_{-\infty}^{\infty}\{\frac{\partial\theta^A(a)}{\partial b}y(\theta^A(a),a)p(\theta^A(a),a)f(\theta^A(a)|a)[b - ry(\theta^A(a),a)]\}dH(a)}{\int_{-\infty}^{\infty}\{\int_{\theta^A(a)}^{\infty}p(\theta,a)dF(\theta|a)\}dH(a)E[E[y(\theta,a)|a]]} \\
&\underbrace{\geq -\tilde{\varepsilon} + \tilde{\mu}\frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|DI,a]]}\frac{b - ry(\theta^A(a_{max}),a_{max})}{b}}_{\text{necessary condition}}.
\end{aligned} \tag{4.138}$$

Moving from Cash Cliff to Benefit Offset: Let us denote the characteristic of the marginal applicant in a cash cliff system with the flattest indifference curve at SGA by a^C_{min}. Consequently, $\theta^A_C(a^C_{min})$ is the disability level of the marginal applicant with the lowest counterfactual labor supply if working. Figure 4A.3 depicts the indifference curve of this limit marginal applicant together with indifference curves of two marginal applicants with random heterogeneity characteristics a_g and a_t.

FIGURE 4A.3. HETEROGENEITY—INTRODUCTION OF MAXIMUM BENEFIT OFFSET.



Note: This figure illustrates the benefit offset scheme which is equivalent to the cash cliff system. The benefit offset r^h is determined by $1 - r^h = \frac{h_z(SGA,\theta^A_C(a^C_{min}),a^C_{min})}{u'(b+SGA)}$.

Again, we can show equivalence between a cash cliff system and a limit benefit offset system. Figure 4A.3 features a sketch of the maximum benefit offset rate r^h that does not affect individuals' optimal behavior as compared to the cash cliff system. The offset rate is given by the slope of the indifference curve of the limit marginal applicant $\theta^A_C(a^C_{min})$ at SGA. This poses as a limit case of the previous section. For $r \to r^h$, we get $\theta^A(a) \to$

$\theta_C^A(a)\,\forall a$, $y(\theta(a),a) \to 0\,\forall a$, and thus $c^B(\theta^A(a),a) \to b + SGA\,\forall a$. The numerator on the LHS of equation 4.138 can be bounded by

$$\begin{aligned}
&\frac{u'(c^B(\theta^A(a_{max}),a_{max})) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} E[E[y(\theta,a)|DI,a]] \qquad (4.139)\\
&\geq E[\frac{u'(c^B(\theta^A(a),a)) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} E[y(\theta,a)|DI,a]]\\
&\geq E[E[\frac{u'(c^B(\theta,a)) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} y(\theta,a)|DI,a]]\\
&\geq E[\frac{u'(b+SGA) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} E[y(\theta,a)|DI,a]]\\
&\geq \frac{u'(c^B(\theta^A(a_{min}),a_{min})) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} E[E[y(\theta,a)|DI,a]].
\end{aligned}$$

By the limits defined above, we can apply the Sandwich theorem to get

$$\lim_{r\to r^h} \frac{E[E[\frac{u'(c^B(\theta,a)) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} y(\theta,a)|DI,a]]}{E[E[y(\theta,a)|DI,a]]} = \frac{u'(b+SGA) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]}. \qquad (4.140)$$

For the limit of the RHS of 4.138, we use

$$\frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|a]]} \leq 1, \qquad (4.141)$$

$$\frac{y(\theta^A(a_{max}),a_{max})}{E[E[y(\theta,a)|a]]} \geq 1, \qquad (4.142)$$

$$\lim_{r\to r^h} \frac{y(\theta^A(a_{min}),a_{min})}{E[E[y(\theta,a)|a]]} = 1, \text{ and} \qquad (4.143)$$

$$\lim_{r\to r^h} \frac{y(\theta^A(a_{max}),a_{max})}{E[E[y(\theta,a)|a]]} = 1. \qquad (4.144)$$

Consequently, the sufficient and the necessary condition converge to the same limit for $r \to r^h$. Hence, we get that $\frac{\partial W}{\partial r} \leq 0$ if

$$\frac{u'(b+SGA) - E[u'(w(a)-\tau)]}{E[u'(w(a)-\tau)]} \geq -\tilde{\varepsilon} + \tilde{\mu}, \qquad (4.145)$$

where the elasticities $\tilde{\varepsilon}$ and $\tilde{\mu}$ can be estimated, as they represent the elasticities in the total population, aggregated over all heterogeneity characteristics a.

One Period Model with Taxes

Setup: In this addition, we show how contemporaneous taxation affects our results. Instead of a two-period model, we have a one-period model where disability hits at the beginning of the period and every individual not receiving DI benefits has to pay taxes.

This means that every individual working without benefits chooses optimal labor supply $z(\theta)$ according to[14]

$$z(\theta) := \arg\max_{z\geq 0} u(z(\theta)-\tau) - h(z,\theta), \tag{4.146}$$

where τ is a lump sum per capita tax rate. Every individual on DI chooses optimal labor supply $z^B(\theta)$ according to

$$z^B(\theta) := \arg\max_{z^B\geq 0} u(c^B(\theta)) - h(z^B,\theta), \tag{4.147}$$

where

$$c^B(\theta) : = \begin{cases} b + z^B(\theta), & \text{if } z^B(\theta) \leq SGA, \\ b + SGA + (1-r)y(\theta), & \text{if } z^B(\theta) > SGA, \end{cases} \tag{4.148}$$

and

$$y(\theta) = \begin{cases} z^B(\theta) - SGA, & \text{if } z^B(\theta) \geq SGA \\ 0, & \text{if } z^B(\theta) < SGA. \end{cases} \tag{4.149}$$

Moreover, everyone with disability $\theta \geq \theta^A$ applies to DI, where θ^A is given by

$$u(z(\theta^A)-\tau) - h(z(\theta^A),\theta^A) = u(c^B(\theta^A)) - h(z^B(\theta^A),\theta^A), \tag{4.150}$$

$$u'(z(\theta^A)-\tau) = h_z(z(\theta^A),\theta^A), \text{ and} \tag{4.151}$$

$$(1-r)u'(c^B(\theta^A)) = h_z(z^B(\theta^A),\theta^A). \tag{4.152}$$

Welfare is given by

$$\begin{aligned} W = & \int_0^{\theta^A} u(z(\theta)-\tau) - h(z(\theta),\theta)dF(\theta) + \int_{\theta^A}^{\infty} p(\theta)[u(c^B(\theta)) - h(z^B(\theta),\theta)]dF(\theta) \\ & + \int_{\theta^A}^{\infty} [1-p(\theta)][u(z(\theta)-\tau) - h(z(\theta),\theta)]dF(\theta) \end{aligned} \tag{4.153}$$

[14] Note that we require one of two conditions to hold for this extension: either (1) $u(z(\theta)-\tau) - h(z(\theta),\theta) \geq 0 \, \forall\theta$ such that everyone paying taxes gets non-negative utility, or (2) there exists some unconditional welfare program as in scenario 1 in the previous section that guarantees non-negative utility to individuals with high θ that are rejected from DI.

The government budget constraint is given by

$$0 = \int_0^{\theta^A} \tau dF(\theta) + \int_{\theta^A}^{\infty} [1 - p(\theta)]\tau dF(\theta) - \int_{\theta^A}^{\infty} p(\theta)[b - ry(\theta)]dF(\theta) \tag{4.154}$$

$$\leftrightarrow \tag{4.155}$$

$$\tau = \frac{\int_{\theta^A}^{\infty} p(\theta)[b - ry(\theta)]dF(\theta)}{\int_0^{\theta^A} dF(\theta) + \int_{\theta^A}^{\infty} 1 - p(\theta)dF(\theta)} := \frac{\Omega}{\chi}, \tag{4.156}$$

where Ω denotes the sum of payments to all DI recipients and χ denotes the fraction of tax-payers in the economy (i.e. non-DI recipients).

Optimal Benefit Offset: A marginal change in the offset rate changes welfare according to

$$\begin{aligned}\frac{\partial W}{\partial r} = &- \int_{\theta^A}^{\infty} p(\theta)u'(c^B(\theta^A))y(\theta)dF(\theta) \\ &- \frac{\partial \tau}{\partial r}[\int_0^{\theta^A} u'(z(\theta) - \tau)dF(\theta) + \int_{\theta^A}^{\infty} [1 - p(\theta)]u'(z(\theta) - \tau)dF(\theta)]\end{aligned} \tag{4.157}$$

with

$$\begin{aligned}\frac{\partial \tau}{\partial r} = &- \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) + \int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r} r dF(\theta) + \frac{\partial \theta^A}{\partial r} p(\theta^A)f(\theta^A)[b - ry(\theta^A)]}{\chi} \\ &- \frac{\frac{\partial \theta^A}{\partial r} f(\theta^A)p(\theta^A)}{\chi}\tau \\ = &- \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) + r\int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r} dF(\theta) + \frac{\partial \theta^A}{\partial r} p(\theta^A)f(\theta^A)[b - ry(\theta^A) + \tau]]}{\chi}.\end{aligned} \tag{4.158}$$

Hence, a decrease in the offset increases welfare (i.e. $\partial W/\partial r \leq 0$) whenever

$$\frac{\int_{\theta^A}^{\infty} p(\theta)u'(c^B(\theta^A))y(\theta)dF(\theta)}{\frac{\int_0^{\theta^A} u'(z(\theta)-\tau)dF(\theta)+\int_{\theta^A}^{\infty}[1-p(\theta)]u'(z(\theta)-\tau)dF(\theta)}{\chi}} \geq \int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) + r\int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta) + \frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A)[b - ry(\theta^A) + \tau] \tag{4.159}$$

$$\leftrightarrow$$

$$\frac{\frac{\int_{\theta^A}^{\infty} p(\theta)u'(c^B(\theta^A))y(\theta)dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}}{\frac{\int_0^{\theta^A} u'(z(\theta)-\tau)dF(\theta)+\int_{\theta^A}^{\infty}[1-p(\theta)]u'(z(\theta)-\tau)dF(\theta)}{\int_0^{\theta^A} dF(\theta)+\int_{\theta^A}^{\infty} 1-p(\theta)dF(\theta)}} \geq \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{p\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} + \frac{r\int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}\frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} + \frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A)\frac{b - ry(\theta^A) + \tau}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} \tag{4.160}$$

$$\leftrightarrow$$

$$\frac{\frac{E[u'(c^B(\theta))y(\theta)|DI]}{E[y(\theta)|DI]} - E[u'(z(\theta)-\tau)|^-DI]}{E[u'(z(\theta)-\tau)|^-DI]} \geq -\varepsilon + \nu\frac{b - ry(\theta^A) + \tau}{E[y(\theta)|DI]}, \tag{4.161}$$

where ε is the earnings elasticity

$$\varepsilon := -\int_{\theta^A}^{\infty} p(\theta)\frac{\partial y(\theta)}{\partial r}dF(\theta)\frac{r}{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}, \tag{4.162}$$

ν is the benefit take-up semi-elasticity with respect to r

$$\begin{aligned}\nu :&= -\frac{\partial \int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{\partial r}\frac{1}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)} \\ &= \frac{\partial \theta^A}{\partial r}p(\theta^A)f(\theta^A)\frac{1}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)},\end{aligned} \tag{4.163}$$

$E[u'(c^B(\theta))y(\theta)|DI]$ is given by

$$E[u'(c^B(\theta))y(\theta)|DI] = \frac{\int_{\theta^A}^{\infty} p(\theta)u'(c^B(\theta^A))y(\theta)dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}, \tag{4.164}$$

$E[u'(z(\theta)-\tau)|^-DI]$ is given by

$$E[u'(z(\theta)-\tau)|^-DI] = \frac{\int_0^{\theta^A} u'(z(\theta)-\tau)dF(\theta) + \int_{\theta^A}^{\infty}[1-p(\theta)]u'(z(\theta)-\tau)dF(\theta)}{\int_0^{\theta^A} dF(\theta) + \int_{\theta^A}^{\infty} 1-p(\theta)dF(\theta)}, \tag{4.165}$$

and $E[y(\theta)|DI]$ is given by

$$E[y(\theta)|DI] = \frac{\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}. \tag{4.166}$$

The condition in equation (4.161) is equivalent to the standard model apart from the tax term $\nu\frac{\tau}{E[y(\theta)|DI]}$ on the RHS. The expected difference of relative marginal utility changes of DI individuals and non-DI individuals divided by the expected excess labor supply of DI individuals are on the LHS, and the earnings elasticity and the take-up semi-elasticity with respect to r are on the RHS. The difference on the RHS stems from the changed cost effect of DI entry: the government has to pay $b - ry(\theta)^A$ to the marginal DI entrant and loses taxes τ.

From the first order condition of the marginal applicant one can derive the optimality condition $0 \overset{!}{=} F := u(c^B(\theta^A)) - h(z^B(\theta^A), \theta^A) - u(z(\theta^A) - \tau) + h(z(\theta^A), \theta^A)$. One can show that $-y(\theta^A)\frac{\partial\theta^A}{\partial b} \geq \frac{\partial\theta^A}{\partial r} \geq -E[y(\theta)|DI]\frac{\partial\theta^A}{\partial b}$. This follows from

$$\frac{\partial\theta^A}{\partial r} = -\frac{F_r + F_\tau\frac{\partial\tau}{\partial r}}{F_{\theta^A}} = \frac{y(\theta^A)u'(c^B(\theta^A)) - u'(z(\theta^A) - \tau)\frac{\partial\tau}{\partial r}}{h_\theta(z(\theta^A), \theta^A) - h_\theta(z^B(\theta^A), \theta^A)}, \tag{4.167}$$

$$\frac{\partial\theta^A}{\partial b} = -\frac{F_b + F_\tau\frac{\partial\tau}{\partial b}}{F_{\theta^A}} = -\frac{u'(c^B(\theta^A)) + u'(z(\theta^A) - \tau)\frac{\partial\tau}{\partial b}}{h_\theta(z(\theta^A), \theta^A) - h_\theta(z^B(\theta^A), \theta^A)}, \tag{4.168}$$

$$\frac{\partial\tau}{\partial r} = \frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A}\frac{\partial\theta^A}{\partial r} - \int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) - \tau\frac{\partial\chi}{\partial\theta^A}\frac{\partial\theta^A}{\partial r}], \text{ and} \tag{4.169}$$

$$\frac{\partial\tau}{\partial b} = \frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A}\frac{\partial\theta^A}{\partial b} + \int_{\theta^A}^{\infty} p(\theta)dF(\theta) - \tau\frac{\partial\chi}{\partial\theta^A}\frac{\partial\theta^A}{\partial b}]. \tag{4.170}$$

Combining the equations yields

$$\frac{\partial\theta^A}{\partial r} = -\frac{F_r + F_\tau \frac{\partial\tau}{\partial r}}{F_{\theta^A}} = -\frac{F_r}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\Big[\frac{\partial\Omega}{\partial\theta^A}\frac{\partial\theta^A}{\partial r} - \int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) - \tau\frac{\partial\chi}{\partial\theta^A}\frac{\partial\theta^A}{\partial r}\Big]$$
$$= -\frac{F_r}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\Big[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}\Big]\frac{\partial\theta^A}{\partial r} + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) \tag{4.171}$$

$$\leftrightarrow$$

$$\frac{\partial\theta^A}{\partial r} = \frac{-\frac{F_r}{F_{\theta^A}} + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]} \text{ and} \tag{4.172}$$

$$\frac{\partial\theta^A}{\partial b} = -\frac{F_b + F_\tau \frac{\partial\tau}{\partial b}}{F_{\theta^A}} = -\frac{F_b}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\Big[\frac{\partial\Omega}{\partial\theta^A}\frac{\partial\theta^A}{\partial b} + \int_{\theta^A}^{\infty} p(\theta)dF(\theta) - \tau\frac{\partial\chi}{\partial\theta^A}\frac{\partial\theta^A}{\partial b}\Big] \tag{4.173}$$
$$= -\frac{F_b}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\Big[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}\Big]\frac{\partial\theta^A}{\partial b} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)dF(\theta)$$

$$\leftrightarrow$$

$$\frac{\partial\theta^A}{\partial b} = \frac{-\frac{F_b}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]}. \tag{4.174}$$

We know that $\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta) \leq y(\theta^A)\int_{\theta^A}^{\infty} p(\theta)dF(\theta)$ as $y(\theta^A) \geq y(\theta)\ \forall\theta \geq \theta^A$, $F_b \geq 0$, and $F_{\theta^A} \geq 0$. Further, we know that $\frac{F_r}{F_{\theta^A}} = -\frac{F_b}{F_{\theta^A}}y(\theta^A)$. Hence, it holds that

$$\frac{\partial\theta^A}{\partial r} = \frac{-\frac{F_r}{F_{\theta^A}} + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]} \tag{4.175}$$
$$= \frac{\frac{F_b}{F_{\theta^A}}y(\theta^A) + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)y(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]}$$
$$\leq \frac{\frac{F_b}{F_{\theta^A}}y(\theta^A) + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}y(\theta^A)\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]} \tag{4.176}$$
$$= -\frac{-\frac{F_b}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}\int_{\theta^A}^{\infty} p(\theta)dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}}\frac{1}{\chi}[\frac{\partial\Omega}{\partial\theta^A} - \tau\frac{\partial\chi}{\partial\theta^A}]}y(\theta^A)$$
$$= -\frac{\partial\theta^A}{\partial b}y(\theta^A). \tag{4.177}$$

Moreover, it follows that

$$\frac{\partial \theta^A}{\partial r} = \frac{\frac{F_b}{F_{\theta^A}} y(\theta^A) + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} \int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} [\frac{\partial \Omega}{\partial \theta^A} - \tau \frac{\partial \chi}{\partial \theta^A}]} \tag{4.178}$$

$$\geq \frac{\frac{F_b}{F_{\theta^A}} \frac{\int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)} + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} \int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} [\frac{\partial \Omega}{\partial \theta^A} - \tau \frac{\partial \chi}{\partial \theta^A}]} \tag{4.179}$$

$$= \frac{\frac{F_b}{F_{\theta^A}} \frac{\int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)} + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} \int_{\theta^A}^{\infty} p(\theta) dF(\theta) \frac{\int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)}}{1 + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} [\frac{\partial \Omega}{\partial \theta^A} - \tau \frac{\partial \chi}{\partial \theta^A}]}$$

$$= -\frac{-\frac{F_b}{F_{\theta^A}} - \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} \int_{\theta^A}^{\infty} p(\theta) dF(\theta)}{1 + \frac{F_\tau}{F_{\theta^A}} \frac{1}{\chi} [\frac{\partial \Omega}{\partial \theta^A} - \tau \frac{\partial \chi}{\partial \theta^A}]} \frac{\int_{\theta^A}^{\infty} p(\theta) y(\theta) dF(\theta)}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)}$$

$$= -\frac{\partial \theta^A}{\partial b} E[y(\theta)|DI]. \tag{4.180}$$

From $-y(\theta^A)\frac{\partial \theta^A}{\partial b} \geq \frac{\partial \theta^A}{\partial r} \geq -E[y(\theta)|DI]\frac{\partial \theta^A}{\partial b}$, we learn that $\mu \frac{E[y(\theta)|DI]}{b} \leq \nu \leq \mu \frac{y(\theta^A)}{b}$, where μ is the benefit take-up elasticity with respect to b

$$\mu := \frac{\partial \int_{\theta^A}^{\infty} p(\theta) dF(\theta)}{\partial b} \frac{b}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)} = -\frac{\partial \theta^A}{\partial b} p(\theta^A) f(\theta^A) \frac{b}{\int_{\theta^A}^{\infty} p(\theta) dF(\theta)}. \tag{4.181}$$

We can insert these bounds into equation (4.161) to get a sufficient condition for $\frac{\partial W}{\partial r} \leq 0$

$$\frac{\frac{E[u'(c^B(\theta)) y(\theta)|DI]}{E[y(\theta)|DI]} - E[u'(z(\theta) - \tau)|^- DI]}{E[u'(z(\theta) - \tau)|^- DI]} \geq -\varepsilon + \mu \frac{b - r y(\theta^A) + \tau}{b} \frac{y(\theta^A)}{E[y(\theta)|DI]}, \tag{4.182}$$

and a necessary condition for $\frac{\partial W}{\partial r} \leq 0$

$$\frac{\frac{E[u'(c^B(\theta)) y(\theta)|DI]}{E[y(\theta)|DI]} - E[u'(z(\theta) - \tau)|^- DI]}{E[u'(z(\theta) - \tau)|^- DI]} \geq -\varepsilon + \mu \frac{b - r y(\theta^A) + \tau}{b}. \tag{4.183}$$

Moving from Cash Cliff to Benefit Offset: Note that lump sum taxes under the cash cliff system are given by $\tau = \frac{\int_{\theta^A}^{\infty} p(\theta) b dF(\theta)}{\int_0^{\infty} dF(\theta) + \int_{\theta^A}^{\infty} [1 - p(\theta)] dF(\theta)} = b \frac{P(DI)}{1 - P(DI)}$. Let us define r^O as the maximum offset rate that makes the cash cliff and the benefit offset systems equivalent. It is determined by $1 - r^O = \frac{h_z(SGA, \theta_C^A)}{u'(b + SGA)}$. For $r \to r^O$, it holds that $\theta^A \to \theta_C^A$ and $y(\theta^A) \to 0$. Consequently, the LHS of equations 4.182 and 4.183 becomes

$$\lim_{r \to r^O} \frac{\frac{E[u'(c^B(\theta) y(\theta)|DI]}{E[y(\theta)|DI]} - E[u'(z(\theta) - \tau)|^- DI]}{E[u'(z(\theta) - \tau)|^- DI]} \tag{4.184}$$

$$= \frac{E[u'(c^B(\theta))|DI] - E[u'(z(\theta) - \tau)|^- DI]}{E[u'(z(\theta) - \tau)|^- DI]},$$

by the sandwich theorem (see the baseline model and the previous additions). Moreover, it holds that

$$\lim_{r \to r^O} \frac{b - ry(\theta^A) + \tau}{b} = \frac{b + \tau}{b} = \frac{b + b\frac{P(DI)}{1-P(DI)}}{b} = \frac{1}{1 - P(DI)}, \text{ and.} \tag{4.185}$$

$$\lim_{r \to r^O} \frac{y(\theta^A)}{E[y(\theta)|DI]} = 1. \tag{4.186}$$

Hence, the conditions in equations 4.182 and 4.183 have the same limit. It follow that $\frac{\partial W}{\partial r} \leq 0$ whenever

$$\frac{E[u'(c^B(\theta))|DI] - E[u'(z(\theta) - \tau)|^{-}DI]}{E[u'(z(\theta) - \tau)|^{-}DI]} \geq -\varepsilon + \mu \frac{1}{1 - P(DI)}. \tag{4.187}$$

Curriculum Vitae

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Education

09/2014–09/2019	Doctoral program at the Zurich Graduate School of Economics, University of Zurich
04/2018–05/2018	Invited research visit at the Centre for Economic Demography, Lund University
04/2018	Invited research visit at the Department of Economics, University of Gothenburg
09/2013–07/2016	Master of Science UZH in Business and Economics, Economics, University of Zurich
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Professional experience

2012–2019	Research assistant to Prof. Ulrich Woitek, University of Zurich
2016–2018	Teaching assistant to Prof. Josef Zweimüller, University of Zurich, Advanced Macroeconomics (MA)
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